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The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market

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Abstract: We analyze the intertemporal stability of excess returns to technical trading rules in the foreign exchange market by conducting true, out-of-sample tests on previously studied rules. The excess returns of the 1970s and 1980s were genuine and not just the result of data mining. But these profit opportunities had disappeared by the early 1990s for filter and moving average rules. Returns to less-studied rules also have declined but have probably not completely disappeared. High volatility prevents precise estimation of mean returns. These regularities are consistent with the Adaptive Markets Hypothesis (Lo, 2004), but not with the Efficient Markets Hypothesis.

JEL Codes: F31, G14, G11

Key words: technical analysis, foreign exchange, structural break, market efficiency, adaptive markets hypothesis

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The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market

I. Introduction

Practitioners use technical analysis extensively to guide trading in financial markets, and many regard it as an essential tool of the trade. But if it enables traders to earn excess risk-adjusted profits, it constitutes evidence inconsistent with financial market efficiency. Academics have therefore scrutinized the performance of technical trading rules (TTRs) as a measure of efficiency. One of the earliest studies, by Fama and Blume (1966), found no evidence that a particular class of TTRs could earn abnormal profits in the stock market. However, more recent research by Brock, Lakonishok and LeBaron (1992) and Sullivan, Timmermann and White (1999) has provided contrary evidence. And studies of the foreign exchange market, where technical analysis is particularly widely used, have long indicated profit opportunities (Poole (1967), Dooley and Shafer (1984), Sweeney (1986), Levich and Thomas (1993), Neely, Weller and Dittmar (1997), Gencay (1999), Maillet and Michel (2000), Lee, Gleason and Mathur (2001), Martin (2001)). Menkhoff and Taylor (2006) and Park and Irwin (2006) both survey and interpret the extensive academic literature on technical analysis in foreign exchange markets.

As evidence against the Efficient Markets Hypothesis (EMH) has accumulated, academics have begun to explore alternatives to the standard model of optimizing agents with rational expectations. Much of this work falls under the heading of behavioral finance. Agents are assumed to be subject to a variety of cognitive biases that have been documented in the psychology literature. Such biases are then shown to explain phenomena for which the standard model cannot easily account. But critics charge that behavioral finance consists of a proliferation of essentially *ad hoc* models designed to explain a few asset pricing "anomalies" and that there is no satisfactory underlying theoretical framework to compare with that of the standard model. Recently Lo (2004) has proposed the Adaptive Markets Hypothesis (AMH) in an effort to develop such a framework. The AMH modifies the EMH view of the world to assert that the forces that drive prices to their efficient levels are weaker and operate over longer time horizons. Processes of learning and competition and evolutionary selection pressures govern these forces. Individual agents are no longer the "hyper-rational" beings of the standard paradigm, but rather boundedly rational "satisficers" in the terminology of Herbert Simon (1955). The AMH paradigm views markets as ecological systems in which different groups or “species” compete for scarce resources. The system will tend to exhibit cycles in which competition depletes existing resources (trading opportunities), but new opportunities then appear. This AMH has three relevant predictions for the present paper. First, profit opportunities will generally exist in financial markets. Second, the forces of learning and competition will gradually erode these profit opportunities. Finally, more complex strategies will persist longer than simple ones.

The extensive work on technical trading in foreign currency markets lends itself to an examination of these predictions of the AMH. Our aim therefore is to consider the evidence that technical trading in foreign exchange has offered excess return opportunities and to look at how those opportunities have changed over time. In particular, we examine the speed with which profit opportunities decline and disappear. This is ultimately an empirical issue that has important implications for the functioning of financial markets. DeLong, Shleifer, Summers and Waldmann (1990) observed that rational arbitrageurs could be exposed to noise trader risk that would limit their short-term ability to correct mispricing, and Shleifer and Vishny (1997) further developed the argument by pointing out that information asymmetries between portfolio managers and investors could weaken the forces of arbitrage precisely when they were most needed. Miscalculation about the speed with which markets would correct mispricing largely drove the 1998 collapse of the hedge fund, Long-Term Capital Management (Lowenstein (2000)).

Several papers have questioned the stability of TTR profits. Levich and Thomas (1993), for example, note that the profits to their technical rules declined in their final subsample, 1986-1990. More recently, LeBaron (2002) evaluated the stability of moving average (MA) returns for three exchange rates with data from 1973 to 2002. LeBaron finds that returns to a 150-day MA trading rule declined in the 1990s and speculates that data snooping might be responsible for earlier successes. He argues that the apparent dynamic instability of the returns to the rules could discourage potential users from exploiting them.

Okunev and White (2003) and Olson (2004), using different optimizing procedures to select MA trading strategies, arrive at different conclusions on their continued profitability. Okunev and White (2003) considered whether momentum strategies in MA rules could continue to produce positive results in the recent era. They found that taking simultaneous long and short positions in MA rules with the best and worst returns over the previous month produced “substantial” returns over the period 1980-2000. The success of their strategies appears to be robust to time periods and other factors.

Olson (2004) dynamically reoptimizes MA rule portfolios in successive 5-year periods from 1971-2000 and then tests these in successive 5-year out-of-sample periods. He finds that returns declined from the 1970s to about zero in the 1990s. Without explicitly citing the AMH, Olson suggests that returns in the 1970s and 1980s might have reflected a temporary inefficiency that is being corrected. And, presaging results in this paper, he concludes that “To ‘beat’ the currency market in the future may require more complicated trading rules, which in turn may represent temporary inefficiencies that will be eliminated once they are identified.”

The present study aims to complement and extend existing work that has evaluated the performance of TTRs. We seek to establish whether the excess returns for particular rules, documented over specific samples, were indeed genuine or the product of data mining. We then characterize how excess returns evolve over time. We approach these questions by selecting rules that prominent papers in the daily TTR literature have previously found to be profitable and then testing their true out-of-sample performance.

This procedure is similar to that employed by Schwert (2002), who found that certain well-known pricing anomalies in the stock market—the size effect, the value effect, the weekend effect, and the dividend yield effect—have weakened or disappeared after they were described in the literature and practitioners began to exploit them. It is also similar to Park and Irwin (2005), who reexamined the performance of technical rules that had been tested on commodities, metals and financial futures data by Lukac, Brorsen, and Irwin (1988) on data from 1978 to 1984. Park and Irwin (2005) find that excess returns do not persist into the period from 1985 to 2003.

We consider the following papers: Sweeney (1986), Levich and Thomas (1993), Taylor (1994), Neely, Weller and Dittmar (1997) (henceforth NWD) and Dueker and Neely (2007). The first three papers selected a small number of rules commonly used by technical traders. They are thus potentially subject to the criticism that the particular rules acquired their popularity simply because of their chance past success. In other words the rules were unconsciously selected by mining past data. If that were the case, then those technical rules would not be expected to perform any better than randomly generated rules in any future time period.

The paper by NWD used a different methodology, designed to minimize the risk of producing spurious results stemming from data mining. The full data sample was subdivided into in-sample and out-of-sample periods and a genetic program identified optimal in-sample rules, whose performance was then measured out-of-sample. In this case, examining an additional out-of-sample period allows us to infer the performance of the trading rules over time.

Dueker and Neely (2007) used a trading rule based on a Markov switching model of interest-adjusted exchange rate returns. They found that incorporating information from higher moments was helpful in modeling expected returns. As in the paper by NWD, the model was first estimated on an in-sample period and then tested on out-of-sample data.

We assess the performance of the trading rules considered in these papers over time periods which start from the end of the original samples. We will refer to these later sample periods as “ex post” to distinguish them from the original samples. The performance of the filter rules examined by Sweeney (1986) deteriorates after 1980, but many rules are still significantly profitable in the ex post period. The same is true of the channel rules and ARIMA rules analyzed by Taylor (1994) and the Markov rules examined by Dueker and Neely (2007). While one cannot reject the hypothesis that the return in the ex post period is zero, neither can one usually reject the null that the mean returns are the same in each sample. In contrast, Levich and Thomas’ (1993) filter and MA rules are no longer profitable in the ex post period (1991-2005:6) and one can easily reject the null that the returns are equal between samples. For all the papers that we consider, the trading rules produce poorer results in the ex post periods.

We go on to examine the evidence in favor of two hypotheses about why the performance of rules has deteriorated over time. The first hypothesis is that the excess returns never really existed and that data mining and publication bias produced their apparent success. Publication bias describes the tendency of academic journals to publish “interesting” or “unusual” results, in this case, findings that contradict the conventional wisdom of efficient markets. The second hypothesis—the AMH—is that the returns were genuine, but that the rules became much less profitable as markets became aware of their existence.

One testable implication of the first hypothesis—data mining—is that TTRs would appear to lose profitability "suddenly" at the point where the original sample ended. In contrast, while the AMH may be consistent with such an observation, it is also consistent with other patterns that depend upon the speed of market adjustment. One of our main aims is to quantify this speed of adjustment. From an econometric point of view, one asks whether a break in mean return or a downward trend in mean return fits the data better. We find little support for the existence of a mean break at the end of the original sample period, other than for the Levich and Thomas (1993) study. This leads us to conclude that the excess returns identified in the 1970s and 1980s were genuine. The rates at which these returns have declined has varied across currencies and across rules.

We complement the tests of structural breaks at the end of the original sample with Andrews' (1993) test for a break at an unknown point. While the Andrews test has less power than a test that correctly prespecifies the break date, it can find breaks at any date. These tests show that while conventional filter and MA rules have almost certainly seen a mean break in return, there is very little evidence that channel rules or econometrically fitted rules from ARIMA models, GP, or Markov models have such a break.

II. Technical Analysis in the Foreign Exchange Market

Technical analysis uses information about historical price movements, summarized in the form of price charts, to forecast future price trends. This approach to forecasting is commonly used to guide trading decisions in the foreign exchange market, and market participants believe that such strategies influence exchange rates. A survey conducted for the Group of Thirty (1985), which covered forty large banks and fifteen securities houses in twelve countries, found that 97 percent of bank respondents and 87 percent of securities houses believed that technical analysis had a significant impact on the foreign exchange market. In a survey of major dealers in the London foreign exchange market, Taylor and Allen (1992) reported that, at short horizons of one week or less, 90 percent of respondents said that they used some form of chartist input, with 60 percent stating that they regarded such information as at least as important as economic fundamentals. A survey of the German foreign exchange market by Menkhoff (1997) produced similar results. Cheung and Chinn (2001) investigated the US market and found that 30 percent of market traders chose technical analysis as the best description of their style of trading. This was higher than any other category, including fundamental analysis, which 25 percent of respondents chose. Surveys of Asian markets by Lui and Mole (1998) and Cheung and Wong (2000) also found that dealers viewed technical analysis as an important tool that was more useful than fundamental analysis in forecasting trends and turning points, particularly at horizons up to six months.

Although these studies reveal that currency traders have long favored technical analysis, they do not disclose what particular rules are used. Further, favored rules almost certainly change over time. Texts on the subject describe broad classes of rules, but even the simplest such classes provide huge variation in the possible rules. For example, a MA rule signals a trade when a "short" MA intersects a "long" MA. But if we allow all possible combinations of short and long moving averages from, say one to two hundred days, this generates 19,900 possible rules. Further, such rules can be augmented with variable sized "bands of inaction," creating still more combinations. The chance that, by searching over all these rules, one may end up with one which performs exceptionally well is clearly considerably higher than the possibility that a single, randomly selected rule will produce the same result. This led White (2000) to propose the "Reality Check" to adjust significance levels in the face of possible data snooping.[1] Our approach in this paper complements that of White (2000) in the following sense: even if one has searched over a given data sample to select a best-performing rule, that rule's performance can be assessed in a second, independent sample with standard tests of significance.

III. Methodology

Both Sweeney (1986) and Levich and Thomas (1993) examine the performance of filter rules, which Fama and Blume (1966) describe. Levich and Thomas also use MA rules. The MA rules buy the foreign currency when a short MA of past exchange rates (dollar price of foreign currency) exceeds a long MA,

[1] Hsu and Kuan (2005) apply White's Reality check in the context of the foreign exchange market.

and sell the currency otherwise. We denote these rules as MA(S, L), where S and L denote the number of days in the short and long MA respectively.

Taylor (1994) reports evidence from channel rules, which take long (short) positions when the price exceeds (goes below) the maximum (minimum) price observed over the previous L days. We will refer to the channel rules as Taylor (C) rules. Taylor also considers ARIMA (1,0,2) trading rules. The ARIMA rules are fit to in-sample data and trade when the expected return exceeds a "band of inactivity." Taylor prespecifies the ARIMA order and chooses the size of the band to maximize in-sample profitability. We will refer to the ARIMA rules as Taylor (A) rules.

NWD (1997), in contrast, identify optimal rules in-sample with genetic programming—a flexible algorithm that searches over a very broad class of possible rules—and then examine the rules' out-of-sample performance.[2] Although not completely immune from the dangers of data mining, this procedure can be interpreted with considerable confidence as a true out-of-sample profitability test.

Dueker and Neely (2007) use a Markov switching model on deviations from uncovered interest parity, with time-varying mean, variance and kurtosis to develop trading rules. In-sample data are used to estimate model parameters and to construct optimal "bands of inactivity" that reduce trading frequency. The rules are then tested on out-of-sample data.

Some of these studies employ slight variations on our procedures, e.g., Levich and Thomas (1993) use futures data; Sweeney (1986) does not permit short positions. While we were able to replicate the original results reasonably well using procedures and data close to those originally employed—replicated results are omitted for brevity—this paper presents results from standardized procedures to ensure comparability across studies.

IV. The Performance Criterion

We now turn to the measure of excess return, which is the performance criterion we use in all of our out-of-sample tests. The rules we examine switch between long and short positions in the foreign

[2] NWD (1997) describe genetic programming in detail.

currency. We suppose that some amount is held in dollars and is reinvested daily at the domestic overnight interest rate. This can be thought of as the margin held against borrowing an amount equal in value, either in dollars (if a short position is held) or the foreign currency. If the trading rule signals a long position in the foreign currency at date t, the borrowed dollars are converted to foreign currency at the closing rate for date t and earn the foreign overnight rate. We denote the exchange rate at date t ($ per unit of foreign currency) by S_t, and the domestic (foreign) overnight interest rate by i_t (i_t^*). Then the excess return, R_{t+1}, to a long position in the foreign currency is given by

(1) $$R_{t+1} = \frac{S_{t+1}}{S_t}\frac{(1+i_t^*)}{(1+i_t)}.$$

We denote the continuously compounded (log) excess return by $z_t r_{t+1}$ where z_t is an indicator variable taking the value +1 for a long position and -1 for a short position, and r_{t+1} is defined as:

(2) $$r_{t+1} = \ln S_{t+1} - \ln S_t + \ln(1+i_t^*) - \ln(1+i_t).$$

The cumulative excess return from a single round-trip trade (go long at date t, go short at date $t+k$), with one-way proportional transaction cost, c, is

(3) $$r_{t,t+k} = \sum_{i=0}^{k-1} r_{t+i} + \ln(1-c) - \ln(1+c)$$

Therefore the cumulative excess return r for a trading rule from time zero to time T is given by:

(4) $$r = \sum_{t=0}^{T-1} z_t r_{t+1} + n\ln\left(\frac{1-c}{1+c}\right)$$

where n is the number of round-trip trades.[3]

The calculated returns are unlevered. In fact, foreign exchange market participants have had enormous leverage available for many years. This capital compounds the mystery of the persistent profitability of technical analysis by reducing liquidity constraints of rational arbitrageurs.

[3] This assumes that c is constant. In the empirical implementation we introduce a linear time trend to capture the decline in transaction costs over the full sample period.

Following the papers that we study, we assume that trades can be made contemporaneously at the observed prices. This is consistent with the empirical trading rule literature using daily data. Experiments with higher frequency data show that delaying trades by a few minutes to an hour after a trading signal is generated does not significantly change the risk-return performance of the rules.

The role of transactions costs in trading rule studies merits some discussion. Frenkel and Levich (1975, 1977) estimate transactions costs in the 15 basis point range for a round-trip covered interest parity transaction in spot and forward markets. These authors calculated transactions costs as those that bounded 95 percent of deviations from covered interest parity. Using more precisely timed data from 1976, McCormick (1979) reduces this estimate to about 10 basis points per round trip. Sweeney (1986) cites these studies in deciding to use a figure of 12.5 basis points for the cost of a round-trip. Levich and Thomas (1993) analyze Chicago Mercantile Exchange futures data, from 1976 to 1990. Using average spreads on foreign exchange contracts of $6.25 to $25 per contract and a brokerage commission of $11 per round-trip transaction, Levich and Thomas calculate transaction costs of 2.5 basis points per futures transaction for a large institution over the period 1976 to 1990. They describe 4 basis points per transaction as more "conservative." Their calculations appear to use the fact that futures contracts have a value of about $100,000 for "typical" values of the exchange rate. On the strength of these calculations, Chang and Osler (1999) and NWD (1997) use 5 basis points per change of position from short to long or vice versa. Since the mid-1990s, electronic trading has lowered transactions costs significantly in many markets, including foreign exchange (see, for example Mizrach and Neely (2006)). Recently, spot market participants have faced spreads of 2 basis points or less, for transactions in the $5 to $50 million range.[4]

In summary, transactions costs for a switch from long to short have declined from about 10 basis points in the 1970s to about 2 basis points in the last few years. Most previous researchers have assumed

[4] The authors thank Mark Hoeman, of Hoeman Capital Management, for very helpful discussions of the realities of technical trading in the foreign exchange market, including discussions of transactions costs.

that transactions costs are constant for sample lengths typically ranging from 3 years to 15 years.[5] When one compares cost-adjusted returns over a long period of time, however, one must account for the fall in transactions costs from 10 points to 2 points over the period 1973 to 2005. We approximate the surely uneven rate of decline in such costs with a simple time trend that assumes costs were 10 basis points per switch of position on January 1, 1973 and declined linearly to 1.88 basis points on June 30, 2005.

If we were to report results for trading rule returns adjusted for the average level of transactions costs during the entire sample period, we would spuriously introduce a decline in performance by penalizing more recent returns too heavily relative to those early in the sample period. To allow the reader to assess the importance of the fall in transactions costs, we provide both gross and net returns for all samples. The difference between the declines in gross and net returns can be attributed to the fall in transactions costs.

Our definition of excess return does not consider the return over a "buy-and-hold" strategy in a reference currency, which some researchers have favored. In our opinion, such a criterion is only appropriate in markets where the asset price has a clearly predictable trend, as is the case in the stock market. Attempts to forecast exchange rate returns over the time horizons relevant for this investigation have met with very little success. In addition, a "buy-and-hold" strategy is not well-defined from the point of view of a global investor. If we consider the exchange rate for the British pound, then the "buy-and-hold" return for a British investor is the negative of that for a U.S. investor, whereas any investor can realize our measure of excess return in either currency.

In addition to raw excess returns, we present two measures of risk-adjusted returns: annualized Sharpe ratios and Jensen's α from CAPM regressions. We then compare the TTR Sharpe ratios to the corresponding Sharpe ratios for a buy-and-hold position in MSCI total return equity indices. We wish to emphasize, however, that the TTR Sharpe ratios need not exceed the equity Sharpe ratios for the former to have value. Because the TTR returns are approximately uncorrelated with the equity returns, the technical positions in the foreign exchange market can significantly improve the risk-return tradeoff of a

[5] Park and Irwin (2005) use variable (segmented) transactions costs in their futures market study.

mixed portfolio (e.g., Neely and Weller (1999)). We illustrate this in Section VIII by examining the performance of portfolios that combine a benchmark stock portfolio with trading rule returns.

While the Sharpe ratio is a widely used univariate measure of the risk-return relation, it has its limitations. In particular, it does not account for higher moments such as skewness or kurtosis[6], or the full joint distribution of the asset return and other variables such as other asset returns or consumption. For this reason, we also adjust for risk with the CAPM. This approach has been commonly used in the literature (Cornell and Dietrich (1978), Sweeney (1986), Taylor (1992), Neely (1997) and NWD (1997). None of these papers found significant systematic risk exposure in foreign exchange TTR returns and the results of this paper confirm that finding.

V. Data

Most researchers, such as Dooley and Shafer (1976) and Sweeney (1986), have studied the returns to trading rules with spot exchange rates, often augmented with interest differentials. Others, such as Taylor (1985) and Levich and Thomas (1993), have used futures prices. Futures prices do not require the calculation of interest differentials, but are more expensive to obtain and available over a shorter time span. Past research has shown, and we have confirmed, that interest-rate adjusted spot rates or futures data produce similar estimates of overall trading rule profitability.

All our analysis uses daily exchange rate data from the Federal Reserve H.10 Statistical Release. The exchange rates used are: Belgian franc (BEF), Canadian dollar (CAD), Deutschemark (DEM), French franc (FRF), Italian lira (ITL), Japanese yen (JPY), Swiss franc (CHF), Swedish krona (SEK), Spanish peseta (ESP), and British pound (GBP), all against the USD. The data span April 1973 through June 2005. DEM/JPY and CHF/GBP cross-rates were computed from the USD rates for the NWD study. For those currencies that were superseded by the euro during the sample, the analysis uses the levels and

[6] Rosenberg (2003) and Schulmeister (2006a) present evidence that trading rule returns in the foreign exchange market are often skewed.

returns implied by the parity with the euro at monetary union. Thus, the Sweeney study exhibits considerable dependence across exchange rates in the post 1999 period.

VI. Results

Sweeney's study is the earliest one we examine, and therefore produces the longest ex post period, 1981 to 2005:6. He looked at the performance of various filter rules for ten currencies over the period 1973:4-1980 (1975-1980 for the DEM). The left-hand panel of Table 1 presents our standardized replication of Sweeney's results—filter rules of 0.5, 1, 2, 3, 4, 5 and 10 percent size—calculated over his original sample, from 1973:4 to 1980. The first row of the table shows the gross annual return (Gross AR) while the second row shows the net annual return (Net AR). Recall that we use transactions costs that decline from 10 basis points on January 1, 1973 to 1.88 basis points on June 30, 2005, for each change of position from long to short or vice versa. The smaller filters generally provide significantly positive excess returns, with the one percent filter having an average net return of 8.61 percent over the 10 exchange rates and outperforming all the other filters in seven out of the ten cases. (Average returns are not shown in the table.) Even the smallest filter of 0.5 percent does fairly well with an average net annual return of 5.45 percent, although it trades frequently and thus incurs higher transaction costs. For the CHF the 0.5 percent filter earns a net excess return of 6.09 percent despite generating almost 51 trades a year. The filter size strongly influences trading frequency for all currencies. Large filters generate fewer trades. For example, the 10 percent filter for the CHF reduces the number of trades to fewer than two a year.

[Insert Table 1 about here]

The univariate risk-adjusted returns from the original sample are also excellent. The average Sharpe ratio, over the ten exchange rates, for the one-percent filter in the original sample is 1.02, with an average standard error of 0.41.[7] (The tables do not display the averages.) Sharpe ratios over 0.5 are very common. These point estimates compare very favorably to the 1974-2005:6 Sharpe ratios (standard errors) for

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[7] We implement Lo's (2002) formulas that account for autocorrelation in returns when constructing the Sharpe ratios and their standard errors. This generally slightly attenuates the ratios.

MSCI total return indices for Germany, Japan, the United Kingdom and the United States, which were 0.30 (0.18), 0.17 (0.18), 0.31 (0.17) and 0.37 (0.18), respectively.

When we consider the performance of the trading rules the ex post period, 1981 through 2005:6 in the right-hand panel of Table 1, we find that annual excess returns are substantially reduced but generally still positive. The net returns to the large filters (4-, 5- and 10-percent) now are rather better than those of the smaller filters and are about equal to their 1973-1980 values, on average. Mean annual excess net return over all currencies for the one percent filter falls to 1.82 percent. Almost all pairs of filters/currencies generate more trades in the second (ex post) sample.

[Insert Table 2 about here]

Table 2 presents the results of portfolio rules that give uniform weight to all the Sweeney filter rules.[8] Over the original sample, 1973:4-1980, the net annual returns for all currencies are positive and statistically significant, averaging 5.11 percent. Sharpe ratios for all currencies are at least 0.68 and average 0.84. Comparing the right-hand to the left-hand panels, the table shows that that uniform portfolio rule performance deteriorates from the original sample to the ex post sample. The average net excess return across the ten currencies falls from 5.11 percent to 2.92 percent. Only for the ITL is performance essentially unchanged. In all other cases net returns are lower, sometimes by margins of more than 5 percent per annum. The average Sharpe ratio falls from 0.84 to 0.41. Although all the returns are positive, one rejects the hypothesis that they are statistically significantly different from zero in only 6 of the 10 cases, despite the much longer sample. But one rejects the hypothesis that the excess returns in the two samples are equal in only 1 of 10 cases, for the GBP, at the five percent (two-sided) level. While the statistical evidence against stable returns is rather weak, the separate tests clearly understate the overall significance of the decline in returns. The quite uniform pattern of deterioration in performance strengthens one's belief that it is real.

[8] The uniform portfolio rule will provide results similar to, but not exactly the same as, averaging the results of rules. This is because simple averaging leads to some double counting of transaction costs.

[Insert Table 3 about here]

Next we consider the results of Levich and Thomas (1993). Their sample period runs from 1976 to 1990. We replicate their filter and MA rule results for four spot exchange rates: DEM, JPY, CHF and GBP. We find (see Table 3) that the same general conclusions emerge as in Sweeney (1986). The one percent filter generally performs best among the filter rules in the original sample, producing net excess returns ranging from 6.22 percent per annum for the CHF to 12.48 percent per annum for the JPY. The average one-percent filter-rule return over all four currencies is 8.47 percent. All excess returns for all currencies and all sizes of filter are positive. The MA rules also do very well in the original period. The MA (5,20) is the best performer, with a mean annual in-sample net return of 9.09 percent. The mean annual returns for the other two filter rules, MA (1,5) and MA(1,200), are 5.73 and 8.33 percent. The average Sharpe ratio across all rules and exchange rates was 0.63. Levich and Thomas' bootstrapping exercise strongly supported the conclusion that the results were very unlikely to have occurred by chance.

The ex post sample (1991 through 2005:6) results tell a rather different story. The one percent filter performs uniformly poorly, particularly so for the CHF, where the annual net excess return is –3.51 percent. The annual excess return for the one percent filter, averaged over all four currencies, is –1.14 percent per annum. Thus if a trader had relied upon the results over the period 1976 to 1990 to select a one-percent filter size, his (equally weighted) four-currency trading return would have declined by (8.47 – (–1.14) =) 9.61 percent per annum. A reliably profitable strategy over the original time period would have lost money over the 1991-2005:6 period. Likewise, the average annual net returns to the three MA rules declined by 7 to 10 percentage points and were mostly negative in the ex post sample. The individual performance of each rule is quite a lot worse. The MA(1, 5) rule does not earn positive returns for any currency, and is marginally significantly negative (–5.91 percent) for the CHF. No MA rule earns positive returns for more than two currencies. Likewise, the overall Sharpe ratio across all currencies and rules was -0.01. The tests of equal mean net returns between the two subsamples reject that hypothesis for 21 of 36 cases, using a one-sided test with a 5 percent critical level.

[Insert Table 4 about here]

Table 4 shows results from uniform portfolio rules for each currency, using the Levich and Thomas (1993) rules. The uniform portfolio rules confirm what was found in Table 3: The mean net returns fall dramatically, by almost 7 percentage points, from the original sample (1976-1990) to the ex post (1991-2005:6) and the difference is always statistically significant. The mean annual return across currencies is negative in the later period (–0.11). Similarly, the average Sharpe ratio fell from 0.90 to -0.02.

[Insert Table 5 about here]

Table 5 compares Taylor's (1994) channel rule results from the original sample, 1982 through 1990, to those in the later sample, 1991 through 2005:6. The pattern is similar to that of the previous papers. Performance in the first period is uniformly strong across currencies, but falls off substantially in the second period: The mean net excess return across currencies falls from 5.74 percent per annum to 1.91 percent. No mean return is significantly greater than zero in the second period. However, the JPY exhibits the only significant structural break *t* statistic, at 2.06. Trading frequency declines from the first to the second period; average trades per year falls from 20.51 to 6.00.

[Insert Table 6 about here]

Table 6 compares Taylor's ARIMA results from the original sample 1979-1987:11 to those from the ex post period, 1987:12-2005:6. The pattern of results is similar to that in Table 5. The annual mean net return across the four exchange rates fell about four percent, from 7.09 percent to 2.97 percent, but evidence for the significance of the change for individual currencies is weak. The Sharpe ratio likewise declined from 0.69 to 0.31 from the first to the second period.

Next we turn to the results of NWD (1997). Table 7 presents information on the annual net excess return for a uniform portfolio rule[9] over the period 1981 to October 1995 for each of four exchange rates against the dollar, and for two cross rates. The annual uniform portfolio rule net excess returns for the DEM/USD and DEM/JPY are 6.10 percent and 4.13 percent respectively; returns are statistically significant for those currencies and positive for all currencies. The average net excess return is 2.94

[9] The uniform portfolio rule attaches equal weight to each of 100 separate rules identified by the genetic program.

percent.[10] All but two of the DEM/USD rules generated positive excess returns, and even the poorest performer in terms of mean return, the GBP/CHF cross rate, produced positive excess returns for 92 of the 100 GP rules. The Sharpe ratio across the six exchange rates was a respectable 0.36.

[Insert Table 7 about here]

Comparing results for the original sample (1981—October 1995) with those from the ex post sample (October 1995 through 2005:6), the average net annual return declines to 0.15 percent while the Sharpe ratio declines to 0.02. Three of the six uniform trading rules earn negative net returns. The only two exchange rates for which the portfolio rules nearly matched previous performance are the DEM/USD and GBP/USD. But only the net excess return (4.68 percent) of the DEM/USD is marginally significantly greater than zero. Yet one cannot reject the hypothesis that the mean returns in the two samples are equal, except marginally in the case of the DEM/JPY, where net excess return fell 5.26 percent per annum. This is a persistent difficulty with evaluating TTRs: highly variable exchange rate returns produce imprecisely estimated annual returns.

[Insert Table 8 about here]

The evidence in Table 8 shows that the Markov switching rules in Dueker and Neely (2007), display the same general pattern of lower returns in the ex post sample (1999-2005:6), excepting the GBP.[11] The mean net return across the four exchange rates falls from 6.24 percent per annum in the original sample to 2.87 percent per annum in the ex post sample. The largest declines were for the JPY (10.5 percent) and

[10] Reported results differ from those in the original paper for three reasons: 1) Uniform portfolio results were not reported in the original paper, rather, results were averaged over rules. 2) T-statistics in the original paper were over the 100 rule returns for each exchange rate, improperly ignoring the dependence between those rules. 3) Transactions costs were calculated as 5 basis points in the original paper, rather than with a declining trend.

[11] The Dueker and Neely (2007) paper estimates Markov parameters using data from 1975-1982/83 and then tests the trading rules from 1982/83 to 2005:6. We consider the period of 1999-2005:6 to be a true out-of-sample period because the earliest version of Dueker and Neely, which was written in 2001, ended the sample in 1998.

CHF (5.74 percent). The JPY is the only case for which we reject the hypothesis that the mean returns in the two samples are equal.

[Insert Table 9 about here]

Tables 2, 4, 5, 6, 7, and 8 show the differences in means between the first sample and the second sample, as well as test statistics of the null of equal means in the two subsamples. A complementary way of examining the decline in returns is to estimate a linear trend in returns over the whole sample. Table 9 shows the results of regressing the annualized, excess, uniform trading rule returns on a constant and a time trend. The coefficient on the time trend can be interpreted as the annual decline in fitted rule returns, in percentage points. For the Sweeney (1986) results (Table 2), the fitted decline ranges from 8 basis points per year for the CAD to 34 basis points for the GBP and CHF, with an overall average of 21 basis points per annum. The time trend coefficients were significant five times at the 5-percent one-sided level. The time trends estimated for the Levich and Thomas rules (Table 4) were statistically significant in three of four cases and indicated that the returns to these rules declined by 24 to 42 basis points per year over the whole sample, 1976-2005:6. For the Taylor (C) and (A) rules (Tables 5 and 6), the trend declines in returns range from 14 to 71 basis points per year, but only two of eight t statistics are greater than 1.64. For the channel rules, the 71 basis point figure for the JPY/USD is statistically significant, while for the ARIMA rules, the GBP/USD has a statistically significant 45 basis negative point trend in returns. The time trends fitted to the NWD uniform rule returns are often very close to zero; five are negative, one is positive. Only the 36 basis point negative trend in the DEM/JPY rule returns is marginally statistically significant, with a t statistic of –1.83. Finally, the estimated trends to the Dueker and Neely (2007) returns range from –0.47 to 0.05, but none are statistically significant.

In summary, the filter and MA rules of Sweeney (1986) and Levich and Thomas (1993) often display significant negative time trends in returns. But it is more difficult to find statistically significant trends in the net returns to the channel, ARIMA, GP and Markov rules. The next section of the paper explores whether such a time trend or a break at the end of original sample fits the return data better. In addition, we consider where the evidence for a break is strongest.

[Insert Table 10 about here]

Up to this point, we have only adjusted for risk with the Sharpe ratio. Table 10 presents evidence on whether the CAPM explains the trading rule returns. The table shows the results of regressing annualized daily average net excess returns on annualized, daily excess returns to a buy-and-hold position in the MSCI for U.S. equities.[12] Almost all of the CAPM betas are negative, albeit small in magnitude; the CAPM model does not explain the trading rule returns. This result is robust to using other international stock indices, such as those from Germany or the United Kingdom, and to testing over subsamples. The low correlation of trading rule returns with stock market indices implies that portfolio strategies can improve their performance by combining the returns. We return to this issue in Section VIII.

VII. Data mining vs. the Adaptive Markets Hypothesis

Our investigation of the out-of-sample performance of previously published, profitable trading rules provides a clear picture. The rules performance has generally deteriorated over time, in some cases to the point where rules are earning significantly negative excess returns. Although the observed decline is by no means always significant for individual currencies, the uniformity of the pattern is striking. We now look more closely at this decline, because it may enable us to distinguish between two alternative explanations for the original findings. The first hypothesis is that data mining produced the apparent returns to the rules. That is, researchers selected particular MA and filter rules to study because they were widely used by technical analysts. But the rules may have become popular precisely because they had performed well, by chance, over some particular historical period. If this explanation were correct then there would be no reason to expect the rules to earn consistently positive excess returns over any future time period. The second hypothesis is the AMH, which holds that market participants have increasingly exploited and diminished the excess returns to technical rules. This hypothesis—though not inconsistent with the sudden extinction of profitability—permits the diminution of profits to depend on the speed with

[12] Monthly total returns and index returns were used to calculate monthly dividend returns, which were interpolated to daily frequency and added to daily index returns to calculate total daily returns on the index.

which the market learns about and exploits the strategies.

These alternative hypotheses suggest a testable difference in the behavior of the returns to TTRs. If the excess returns were the result of data snooping, then one should observe a simple break in the mean return at the end of the original sample period. Under the AMH, however, a downward trend or a break at another time would be additional possibilities.

A. Constant mean versus a time trend and a structural break

To investigate which hypothesis is more consistent with the data, we fit three ARIMA(1,0,1) models to the trading rule returns data: 1) a constant mean over the entire sample; 2) a break in mean at the end of the original sample; and 3) a time trend in the mean. Table 11 shows the results of fitting these models to all trading rule returns.

[Insert Table 11 about here]

The left-hand panel shows the difference in Schwarz criterion (SC) between each model and the best model, which will have a normalized SC of zero. Inference from the SC is almost uniform: The constant mean model fits the data best in all cases but one. A parsimonious model selection criterion coupled with high variation in trading rule returns makes a constant return the model that fits best.

The right-hand panel reports the results of applying a two-step selection procedure. First, choose between the (equally parameterized) mean break and time trend models on the basis of log likelihood. Second, test for rejection of the hypothesis that the best model is one with a constant mean. The significance level is set at five percent.[13] If one is unable to reject that hypothesis, the constant mean model is accepted. Otherwise, the better of the mean break or time trend models is chosen. The columns headed "constant", "mean break" and "time trend" report twice the difference in log likelihoods between each model and the best model for that case. The more general mean break or time trend models always have the highest log likelihoods, as one would expect. The final column, labeled "BestH0" describes the

[13] The actual significance level will differ from the nominal significance level because of the pre-test estimator problem: The unrestricted model is chosen as the better of the mean-break and time-trend models.

inference from the two-step procedure. The procedure tends to choose a constant mean (8 times) or a time trend (2 times) for the Sweeney cases. The procedure chooses mean break in all four of the Levich and Thomas cases, but a constant return for 3 of the 4 Taylor channel and all the ARIMA rules, as well as for all the NWD cases. The procedure also picks a constant mean in 3 of the 4 Dueker/Neely cases.

In summary, the two-step selection procedure most often picks a constant mean. However, for the Sweeney cases, where the ex post sample period included the 1980s, returns were best described by a time trend for two of the four currencies considered. The procedure selected a mean break for the Levich and Thomas sample periods in all cases, providing strong evidence for a decline in returns between the period up to 1990 and the subsequent period. The existence of large declines in mean returns is indicative of structural breaks in those series. One can examine where those breaks were mostly likely to have occurred with a test for a structural break at an unknown point.

B. Testing for a structural break at an unknown point

The previous tests for a structural break assumed that the break would be at the end of the original sample, because data mining created spurious returns in the earlier period. The Andrews (1993) test for a structural break at an unknown point provides an alternative perspective on the issue.[14] Although such tests have less power than a test for a break at a correctly pre-specified time, they complement previous tests by providing additional evidence on structural instability, unrelated to data mining.

Specifically, the Andrews (1993) procedure tests for a structural break in the mean return, versus the null of no breaks, in the middle 70 percent of a given sample. The test requires an assumed model and critical values calculated from a Monte Carlo experiment. In the present case, we assume that the data generating process for the uniformly weighted trading rule return, for each study, is a constant plus an

[14] Ghysels, Guay and Hall (1998) propose a less computationally demanding approach than Andrews (1993); the former only estimates the model on the first part of the sample. The simplicity of the constant-return and AR models mitigates this advantage. Similarly, one could test for multiple breaks using the methods of Bai (1997), but these procedures are unlikely to find multiple breaks with such noisy data.

independent and identically distributed error term.[15]

For each type of study, the beginning of the sample period for the Andrews tests was either the beginning of the original sample (Sweeney, Taylor (C), Taylor (A), Levich and Thomas) or—for those papers using econometric estimation—the beginning of the out-of-sample period in the original paper (NWD and Dueker and Neely). The sample starting points were as follows: Sweeney: 4/2/1973; Taylor (C): 1/4/1982; Taylor (A): 1/4/1979; Levich and Thomas: 1/2/1976; NWD: 1/2/1981; and Dueker and Neely: 1/3/1983. All samples ended in June 2005.

[Insert Table 12 about here]

Table 12 displays the results of these Andrews' (1993) tests for a structural break in a constant mean return at an unknown point. The table shows that there is a lot of evidence for structural breaks in the filter rules tested by Sweeney and the filter/MA rules tested by Levich and Thomas. Most these structural breaks in the returns to traditional technical rules are in the 1989 to 1993 period. The GBP and JPY show evidence of breaks in the returns to the Sweeney, Levich and Thomas and Taylor (A) rules. The GBP break dates occur near the infamous speculative episode of "Black Wednesday" (September 16, 1992) when sterling exited the Exchange Rate Mechanism of the European Monetary System. The JPY break dates are all in 1999, after the 1997 Asian currency crisis and the Russian default of 1998. There also seems to be a 1985 break in the returns to the NWD CHF rule.

There is very little evidence of structural breaks in the returns to Taylor's channel rules, NWD's genetic programming rules or Dueker and Neely's Markov rules. We note that the NWD genetic programming and Dueker-Neely Markov models are more complex models than traditional MA or filter rules because they require non-trivial programming skills to estimate and implement. Further, they are not traditional textbook technical models. In other words, one could expect someone with an MBA to

[15] Full details of the Andrews procedure are omitted for brevity, but available from the authors on request. Results with an AR(5) process were very similar to those presented from the i.i.d. process.

analyze the profitability of MA or filter rules in Excel, using historical data, but one could not expect the same person to develop, program, estimate and evaluate the genetic programming or Markov rules.

[Insert Figure 1 about here]

The Andrews' (1993) test illustrates that inference about the presence of breaks depends on the type of rule and sample period considered. Breaks are most prevalent for filter rules whose performance is measured over the longest time period, starting in 1973 (Sweeney) or 1976 (Levich and Thomas). Figure 1 illustrates the noisy nature of the returns in a case in which the test rejects structural stability, the uniform portfolio rule returns to Levich and Thomas' (1993) rules over the period 1976-2005:6. The figure shows that backward-looking one-year rolling returns clearly have a lower mean in the ex post sample than in the original. The straight diagonal lines, which represent predicted values from a time trend model of trading rule returns, illustrate the trend decline in profitability over time. Recall that Table 11 showed that a mean break at the end of 1990 fit the Levich and Thomas data better than a declining time trend, which, in turn, fit well enough to reject a constant mean in 3 of 4 cases (see Table 9).

Figure 1 illustrates that the initial sample period contained only rather short intervals when the trading rules incurred losses and these were generally not large. The situation changes completely as we move into the more recent past. The intervals over which the rules make losses are much more prolonged and the magnitude of the losses increases. Plots for returns to the MA rules are qualitatively very similar. This visually confirms the conclusion drawn from Table 4, that any profit opportunities associated with this combination of MA and filter rules had disappeared by the early 1990s.

VIII. Discussion

The widespread use of technical analysis in the foreign exchange market presents the EMH with something of a paradox. If the EMH reasonably characterizes the data, then another form of gross economic inefficiency must be present in the system to explain why large numbers of foreign exchange traders are handsomely compensated for applying various technical trading systems to no positive effect. The AMH, proposed by Lo (2004), provides a way of resolving this paradox as well as a framework within which one can make sense of the empirical results of this paper. Our findings suggest two broad conclusions. First, positive excess return opportunities have persisted for considerable periods and are not the result of data mining. Second, investment strategies which generate periods of excess returns eventually fall into disuse as competitive pressures erode profits. Both these conclusions indicate that markets deviate substantially from the EMH. In addition, more complex strategies appear to survive longer than simple strategies. This too is what one would expect to observe in a world where markets function as adaptive systems.

In the present context, rather than setting up an extreme version of the EMH as a straw man, it is useful to think of market efficiency as a continuous variable. It will depend on the magnitude of any profit opportunities and the length of time for which they persist. Fairly efficient markets have profit opportunities that are "small" and do not last "too long." But our findings point to noteworthy deviations from perfect efficiency on both counts. Excess returns were substantial and did not disappear for a long time. Advocates of the EMH sometimes argue that observed excess returns simply provide evidence of an as yet unidentified risk factor. But an unidentified risk factor that disappears for unexplained reasons is an unattractive feature of a theory that claims to be falsifiable.

At present, the AMH is far from being a unified theory capable of generating sharp predictions. It provides some guidance on possible causal factors that may explain our results but without further argument is unsatisfactory on its own. For this reason we consider several facts in more detail. We examine first the fact that profit opportunities persisted for a long period of time. Similar phenomena have been documented in the stock market. Banz (1981) showed that small-capitalization firms on the New York Stock Exchange (NYSE) earned substantial excess returns over the period 1936-75. But Horowitz, Loughran and Savin (2000) find no evidence to support the continuing existence of this effect in data from the NYSE, Amex and NASDAQ during 1980-1996, the period after the dissemination of Banz's findings. Similarly, French (1980) found that the return to the S&P composite portfolio over the period 1953-1977 was significantly negative for Monday. This became known as the "weekend effect". Schwert (2002), however, shows that the effect was present for the period starting in 1885 (using Dow Jones portfolios for 1885-1927), but was no longer there for 1978-2002. Again, its disappearance coincides with the date of an academic publication describing the effect. The fact that the effect existed during the earlier sample periods is very strong evidence that it was not simply the result of data snooping. These examples illustrate that simple price inefficiencies can apparently survive for a very long time before they are generally recognized. However, they provide only indirect evidence on the speed with which the inefficiency disappears once publicized. Schwert (2002) cites the case of Dimensional Fund Advisors (DFA), founded in 1981. One of its portfolios, the US 9-10 Small Company Portfolio was constructed specifically to take advantage of the small-firm effect. Over the period 1982-2002 the alpha of the portfolio has not been significantly different from zero, and was actually negative during 1982-1987, suggesting a rather rapid dissipation of potential profits after the publication of Banz (1981).

In the present case, there was evidence of excess returns to TTRs in foreign exchange markets even before Sweeney (1986). For example, Poole (1967), Dooley and Shafer (1976, 1984), and Logue and Sweeney (1977) presented evidence that filter rules were profitable over relatively short samples. Cornell and Dietrich (1978) also presented positive evidence on filter and MA rules. Academic economists, however, were very skeptical of these findings. In a private communication, Jeffrey Shafer informed us that prominent academics were very skeptical, even outright disbelieving, of the findings of Dooley and Shafer (1976 and 1984), for example. The dominant view was that the results must be incorrect or specific to one sample.

[Insert Table 13 about here]

If one dates a general awareness of the profitability of filter rules to 1986, the publication date of Sweeney's paper, we find that profits appear to have survived for several years after that. But, by the publication of Levich and Thomas (1993), they had disappeared. To provide additional evidence on the speed of information dissemination, Table 13 presents a citation count for all the papers we have examined. The Web of Knowledge was used to search the Social Science Citation Index for 1995 to the present, while Dialogue was used to search from 1986 to 1995. To supplement the pre-1996 electronic search—which produced sparse results—we manually searched all of the pre-1996 articles cited by

Menkhoff and Taylor's (2006) excellent literature survey. While this procedure surely misses some citations, it provides a rough estimate of the attention that the papers drew over time.

We see that Sweeney's paper did not attract much attention until 1992, having only four citations up to that point. From then on, Sweeney (1986) and Levich and Thomas (1993) attracted a similar amount of attention. After 2003 interest seemed to shift to NWD (1997). Taylor (1994) has only garnered a modest amount of attention, perhaps explaining the tendency of ARIMA and channel rules to retain some profitability. Although citation counts provide only a crude estimate of the rate at which information spreads, they support the argument that awareness of profit opportunities developed rather slowly.

Two features of the excess returns to trading rules render them particularly attractive investment vehicles: their low correlation with the stock market and their low volatility relative to the stock market. This implies that the full benefit of investing in a TTR strategy in the foreign exchange market requires the investor to form a portfolio with optimal weights attached to the stock portfolio and the foreign exchange trading strategy. We illustrate this by calculating the increase in excess return that a mean-variance investor would have earned if he had split his wealth optimally between a diversified stock portfolio and the foreign exchange trading strategy, holding a portfolio with the same standard deviation as the stock portfolio. We also calculate the portfolio weights to determine the extent to which the optimal portfolio was levered. The matrix of equity and trading rule returns is as follows:

$$r = (r_M, r_T) \tag{5}$$

where r_M and r_T are the vectors of excess returns of the market portfolio and the trading strategy, respectively. If V is the (2x2) covariance matrix of excess returns of the market portfolio and the trading strategy, then the optimal portfolio weight vector, w, on the risky assets, is given by:

$$w = \frac{r_O}{r' V^{-1} r} V^{-1} r \ , \tag{6}$$

where r_O is the total excess return on the optimal portfolio with standard deviation equal to that of the market portfolio, σ_M. The total excess return on the optimal portfolio, r_O, is given by the following:

(7) $$r_O = \sigma_M \sqrt{r'V^{-1}r}\ .$$

[Insert Table 14 about here]

Table 14 presents the results of applying this analysis to the excess returns from the equally weighted portfolio rules reported in Table 4 and the returns to the MSCI US stock index. Over the period 1976-1990 the optimal portfolio combining returns for the JPY with the MSCI index earns an annual excess return of 19.81 percent. The average excess return over the four currencies is 15.69 percent. Similarly, the average Sharpe ratio for the combined portfolio was 0.96, about three times that of the U.S. equity portfolio over the same sample (0.34). The portfolio weight on the trading rule excess return ranges from 1.74 for CHF to 2.26 for JPY. These high weights provide a possible rationale for the often rather high levels of leverage observed for foreign currency positions.

Using the same weights over the more recent period (1991-2005:6) produces an average excess return of 2.94 percent, substantially below the MSCI return of 8.43 percent and the optimal portfolio's Sharpe ratio is only 0.19. Comparing in-sample with out-of-sample optimal returns exaggerates the difference between them because we used the in-sample period to choose optimal weights. Nevertheless, over the earlier period, the combined portfolio would have enhanced the attractiveness of the trading rules, whereas these filter and MA trading rules would probably have been unhelpful in the more recent period.

Simply comparing the excess returns from a diversified stock portfolio to those from a trading rule strategy, rather than computing optimal combined portfolio results, would not have made it clear that the trading rule was an attractive investment opportunity. Neither Sweeney nor Levich and Thomas present their results in such a way as to indicate that a trading rule strategy would be superior to investing in a diversified stock portfolio. Sweeney concentrates on establishing that excess returns are significantly greater than zero, but presents no Sharpe ratios. The average annual excess return over the six currencies he examines is 7.45 percent, close to the postwar equity premium in the United States. Levich and Thomas have a similar emphasis and report average annual excess returns of 6.17 percent for filter rules and 6.73 for MA rules. Even comparing Sharpe ratios from the TTRs to those from equities would not have generated great confidence in the outright superiority of the former. Although the Sharpe ratios that we report above from Sweeney's original sample period are much higher than those from various stock indices, the sample period is comparatively short and precludes a conclusion about superiority.

In addition it is plausible that both institutional and behavioral factors initially militated against the exploitation of the combined portfolio strategy. The bulk of foreign exchange trading is tightly compartmentalized and conducted at intraday frequency. But the best performing GP rules from NWD traded relatively infrequently, roughly every two months. Neither the typical foreign exchange nor equity trading operation would have been well positioned to exploit the portfolio strategy. It would take the increased flexibility of institutions such as hedge funds to do this. The number of hedge funds exploded in the early 1990s (see Table 1 of Hsieh and Fung (1999)), coinciding with the disappearance of daily filter and MA profits in the foreign exchange market.

Another possible contributory factor is the process Thaler (1985) has termed *mental accounting*. This refers to the tendency on the part of investors to evaluate gains and losses in separate accounts rather than consolidating them. Barberis and Huang (2001) have suggested that this process, applied to gains and losses from holding individual stocks and coupled with loss aversion, might at least partially explain a variety of stock market phenomena, including the value premium. If investors approached gains and losses from stock and currency portfolios in the same way, by evaluating them separately and in isolation, this would have prevented them from perceiving the advantage associated with the combined strategy. Camerer and Loewenstein (2004) document that the investment community takes loss aversion seriously. They report how an investment banker had described the way in which his firm combated the effects of loss-aversion by forcing a trader periodically to switch positions with that of another trader. "Switching ensures that traders do not make bad trades because of loss-aversion and emotional attachment to their past trades" (Camerer and Loewenstein (2004), p.17).

Hong and Stein (1999) develop a model in which slow information diffusion coupled with bounded rationality creates persistent price trends from which trend chasers can profit. Schulmeister (2006a) presents a model with some similar features: news creates exchange rate movements that trigger trading signals from heterogeneous rules and the ensuing trades reinforce the initial exchange rate movement. That is, there is mutual feedback between trading rule signals and exchange rate movements. Although both papers provide support for the observation that trading profits can survive for long periods of time, neither gives any direct clue as to what factors, if any, lead to their ultimate disappearance.

Another argument that is sometimes advanced to explain the success of technical trading in foreign exchange is that intervention by monetary authorities leads to predictable moves in the exchange rate that trading rules can take advantage of (Friedman (1953), Sweeney (1986), and Kritzman (1989)). The fact that technical rules seem to be less useful in equity and commodity markets—where there is no intervention—buttressed the argument (Silber (1994)).

More recently, LeBaron (1999) found a high degree of correlation between daily U.S. official intervention and returns to a typical MA rule. When one removed intervention days from the trading rule return series, the mean return became insignificantly different from zero. If this evidence is interpreted to show that intervention by the Federal Reserve is indeed the source of technical trading profits, then the fact that intervention declined dramatically over the course of the 1990s might explain our findings.[16] But Neely (2002) used higher frequency data to show that almost all the returns on the day of intervention occurred overnight, before intervention could plausibly have occurred. The timing and signs of intervention and the trading rule indicate that intervention responded to strong overnight trends (leaning against the wind), from which trading rules profited. In other words, intervention does not generate technical trading returns, but rather responds to strong trends from which technical traders profit. Therefore the observed decline in the frequency of intervention cannot be used to explain our results.

IX. Conclusion

We have examined the evolution over time of the excess returns earned by several broad classes of TTR in the foreign exchange market. Our evidence supports the conclusion that the returns originally documented in a number of papers were genuine and not due to data mining (Sweeney (1986), Levich and

[16] The U.S. authorities intervened 281 times from January 1, 1986 to January 1, 1996, but only twice since then.

Thomas (1993), Taylor (1994), NWD (1997), Dueker and Neely (2007)). We also show that these excess returns declined over time, but at a much slower speed than would be consistent with efficient markets. There was evidence of a mean break to lower returns near the publication of Levich and Thomas (1993), but that seems to be because that study's sample ended approximately coincidentally with the break. Andrews' (1993) test for a structural break at an unknown point indicates that such a break probably occurred in the early 1990s for the most commonly known filter and MA rules. By the mid-1990s, profit opportunities had largely disappeared for these popular classes of rules.

We emphasize that the decline in profitability of MA and filter rules does not mean that TTRs are generally unprofitable.[17] Returns to less-studied or more complex rules, such as channel rules, ARIMA models, genetic programming and Markov models also seem to have declined, but have probably not completely disappeared. Despite this drop in mean returns, the volatility of returns often prevents us from definitely concluding that mean trading rule returns have changed, although that is more likely than not.

Econometrically speaking, one's conclusion about the stability of mean returns to the uniform portfolio rules is sensitive to the methodology used and the particular study. The Schwartz criterion prefers a constant mean across samples. But this reflects the SC's strong preference for parsimony. Sequential LR tests often reject the constant mean for a time trend or mean break for filter and MA rules, but generally not for other rules, such as channel, ARIMA, genetic programming and Markov rules.

Our findings are consistent with a view of markets as adaptive systems subject to evolutionary selection pressures. The rather slow speed with which the market appeared to take advantage of the documented profit opportunities may be explained in part by the fact that an effective investment strategy required trading rule returns to be combined with a diversified stock portfolio. We conjecture that both institutional and behavioral factors might have delayed the implementation of such strategies.

[17] Traders also continue to widely use and presumably profit from high-frequency technical trading rules. Indeed, automated trading has increased greatly in recent years. Consistent with this fact, Schulmeister (2006b) argues that dynamic optimization of common rules shows that intraday rules have become more profitable in equity markets.

References

Andrews, D. "Tests for Parameter Instability and Structural Change with Unknown Change Point." *Econometrica*, 61 (1993), 821-856.

Bai, J. "Estimating multiple breaks one at a time." *Econometric Theory*, 13 (1997), 315-352.

Banz, R. "The Relationship Between Return and Market Value of Common Stock." *Journal of Financial Economics*, 9 (1981), 3-18.

Barberis, N., and M. Huang. "Mental Accounting, Loss Aversion and Individual Stock Returns." *Journal of Finance*, 56 (2001), 1247-1292.

Brock, W., J. Lakonishok, and B. LeBaron. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *Journal of Finance*, 47 (1992), 1731-1764.

Camerer, C. F., and G. Loewenstein. "Behavioral Economics: Past, Present and Future." In *Advances in Behavioral Economics*, C. F. Camerer, G. Loewenstein and M. Rabin, eds. Princeton, NJ: Princeton University Press (2004).

Chang, P., and C. Osler. "Methodical Madness: Technical Analysis and the Irrationality of Exchange-Rate Forecasts." *Economic Journal*, 109 (1999), 636-661.

Cheung, Y., and M. Chinn. "Currency Traders and Exchange Rate Dynamics: A Survey of the US Market." *Journal of International Money and Finance*, 20 (2001), 439-471.

Cheung, Y., and C. Y. Wong. "A Survey of Market Practitioners' Views on Exchange Rate Dynamics." *Journal of International Economics*, 51 (2000), 401-419.

Cornell, W. B., and J. K. Dietrich. "The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates." *Review of Economics and Statistics*, 6 (1978), 111-120.

De Long, J. B., A. Shleifer, L. Summers, and R. Waldmann. "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance*, 45 (1990), 379-395.

Dooley, M. P., and J. R. Shafer. "Analysis of Short-Run Exchange Rate Behaviour: March 1973 to September 1975." Federal Reserve Board, International Finance Discussion Paper, No. 123, (1976).

Dooley, M. P., and J. Shafer. "Analysis of Short-run Exchange Rate Behavior: March 1973 to November 1981." Floating Exchange Rates and the State of World Trade Payments, OECD (1984), 43-69.

Dueker, M., and C. J. Neely. "Can Markov switching models predict excess foreign exchange returns?" *Journal of Banking and Finance,* 31 (2007), 279–296.

Fama, E. F., and M. Blume. "Filter Rules and Stock Market Trading Profits." *Journal of Business*, 39 (1966), 226-241.

French, K. R. "Stock Returns and the Weekend Effect." *Journal of Financial Economics*, 8 (1980), 55-69.

Frenkel, J. A., and R. M. Levich. "Covered Interest Arbitrage: Unexploited Profits?" *Journal of Political Economy*, 83 (1975), 325-338.

Frenkel, J. A., and R. M. Levich. "Transaction Costs and Interest Arbitrage: Tranquil versus Turbulent Periods." *The Journal of Political Economy*, 85 (1977), 1209-1226.

Friedman, M. *The Case for Flexible Exchange Rates, Essays in Positive Economics*. Chicago, IL: University of Chicago Press (1953).

Gencay, R. "Linear, Non-Linear and Essential Foreign Exchange Rate Prediction with Simple Technical Trading Rules." *Journal of International Economics*, 47 (1999), 91-107.

Ghysels, E., A. Guay, and A. Hall. "Predictive Tests for Structural Change with Unknown Breakpoint." *Journal of Econometrics*, 82 (1998), 209-233.

Group of Thirty. "The Foreign Exchange Market in the 1980s." In *Report of the Foreign Exchange Market Study Group*, New York, NY: Group of Thirty (1985).

Hong, H., and J. C. Stein. "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets." *Journal of Finance,* 54 (1999), 2143-2184.

Horowitz, J. L., T. Loughran, and N. E. Savin. "Three Analyses of the Firm Size Premium." *Journal of Empirical Finance*, 7 (2000), 143-153.

Hsieh, D., and W. Fung. "A Primer on Hedge Funds." *Journal of Empirical Finance*, 6 (1999), 309-331.

Hsu, P., and C. Kuan. "Reexamining the Profitability of Technical Analysis with Data Snooping Checks." *Journal of Financial Econometrics*, 3 (2005), 606-628.

Kritzman, M. “Serial dependence in currency returns: investment implications.” *Journal of Portfolio Management*, 16 (1989), 96-102.

LeBaron, B. “Technical trading rule profitability and foreign exchange intervention.” *Journal of International Economics*, 49 (1999), 125-143.

LeBaron, B. “Technical Trading Profitability in Foreign Exchange Markets in the 1990's.” Unpublished manuscript, Brandeis University, (2002).

Lee, C., K. Gleason, and I. Mathur. “Trading Rule Profits in Latin American Currency Spot Rates.” *International Review of Financial Analysis*, 10 (2001), 135-156.

Levich, R. M., and L. R. Thomas, III. “The Significance of Technical Trading-Rule Profits in the Foreign Exchange Market: A Bootstrap Approach.” *Journal of International Money and Finance*, 12 (1993), 451-474.

Lo, A. W. “The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective.” *Journal of Portfolio Management*, 30th Anniversary Issue (2004), 15-29.

Lo, A. W. “The statistics of Sharpe Ratios.” *Financial Analysts Journal*, 58 (2002), 36-52.

Logue, D. E., and R. J. Sweeney. “White Noise in Imperfect Markets: The Case of the Franc/Dollar Exchange Rate.” *Journal of Finance*, 32 (1977), 761-768.

Lowenstein, R. *When Genius Failed: The Rise and Fall of Long-Term Capital Management*. New York, NY: Random House (2000).

Lui, Y., and D. Mole. “The Use of Fundamentals and Technical Analyses by Foreign Exchange Dealers: Hong Kong Evidence.” *Journal of International Money and Finance*, 17 (1998), 535-545.

Lukac, L. P., B. W. Brorsen, and S. H. Irwin. “Similarity of Computer Guided Technical Trading Systems.” *Journal of Futures Markets*, 8 (1988), 1-13.

Maillet, B., and T. Michel. “Further Insights on the Puzzle of Technical Analysis Profitability.” *European Journal of Finance*, 6 (2000), 196-224.

Martin, A. D. "Technical trading rules in the spot foreign exchange markets of developing countries." *Journal of Multinational Financial Management*, 11 (2001), 59-68.

McCormick, F. “Covered interest arbitrage: Unexploited profits: Comment.” *Journal of Political Economy*, 87 (1979), 411-417.

Menkhoff, L. “Examining the Use of Technical Currency Analysis.” *International Journal of Finance and Economics*, 2 (1997), 307-318.

Menkhoff, L., and M. P. Taylor. “The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis.” Unpublished manuscript, University of Warwick, (2006).

Mizrach, B., and C. J. Neely. “The Transition to Electronic Communications Networks in the Secondary Treasury Market.” Federal Reserve Bank of St. Louis *Review*, 88 (2006), 527-542.

Neely, C. J. “Technical Analysis in the Foreign Exchange Market: A Layman's Guide.” Federal Reserve Bank of St. Louis *Review*, 79 (1997), 23-38.

Neely, C. J. “The Temporal Pattern of Trading Rule Returns and Exchange Rate Intervention: Intervention Does Not Generate Technical Trading Rule Profits.” *Journal of International Economics*, 58 (2002), 211-232.

Neely, C. J., and P. Weller. “Technical Trading Rules in the European Monetary System.” *The Journal of International Money and Finance*, 18 (1999), 429-458.

Neely, C. J., P. Weller, and R. Dittmar. “Is Technical Analysis in the Foreign Exchange Market Profitable? A Genetic Programming Approach.” *Journal of Financial and Quantitative Analysis*, 32 (1997), 405-426.

Okunev, J., and D. White. “Do Momentum Strategies Still Work in Foreign Currency Markets?” *Journal of Financial and Quantitative Analysis*, 38 (2003), 425-447.

Olson, D. “Have trading rule profits in the currency markets declined over time?” *Journal of Banking and Finance*, 28 (2004), 85–105.

Park, C., and S. H. Irwin. “The Profitability of Technical Trading Rules in US Futures Markets: A Data Snooping Free Test.” AgMAS Project Research Report 2005-04, (2005).

Park, C., and S. H. Irwin. “What Do We Know about the Profitability of Technical Analysis?” forthcoming in *Journal of Economic Surveys,* (2006).

Poole, W. "Speculative Prices as Random Walks: An Analysis of Ten Time Series of Flexible Exchange Rates." *Southern Economic Journal*, 33 (1967), 468-478.

Rosenberg, M. R. *Exchange Rate Determination: Models and Strategies for Exchange Rate Forecasting*. New York, NY: McGraw-Hill (2003).

Schulmeister, S. "The Interaction Between Technical Currency Trading and Exchange Rate Fluctuations." *Finance Research Letters,* 3 (2006a), 212-233.

Schulmeister, Stephan. "The Profitability of Technical Stock Trading Has Moved from Daily to Intraday Data." Unpublished manuscript, Austrian Research Institute, (2006b).

Schwert, G. W. "Anomalies and Market Efficiency." National Bureau of Economic Research, NBER Working Papers: 9277, (2002).

Shleifer, A., and R. Vishny. "The Limits of Arbitrage." *Journal of Finance*, 52 (1997), 35-55.

Silber, W. "Technical trading: when it works and when it doesn't." *Journal of Derivatives*, 1 (1994), 39-44.

Simon, H. "A Behavioral Model of Rational Choice." *Quarterly Journal of Economics,* 69 (1955), 99-118.

Sweeney, R. J. "Beating the Foreign Exchange Market." *Journal of Finance*, 41(1986), 163-182.

Sullivan, R., A. Timmermann, and H. White. "Data-Snooping, Technical Trading Rule performance, and the Bootstrap." *Journal of Finance*, 54 (1999), 1647-1691.

Taylor, M. P., and H. Allen. "The Use of Technical Analysis in the Foreign Exchange Market." *Journal of International Money and Financ*e, 11 (1992), 304-314.

Taylor, S. J. "The behaviour of futures prices over time." *Applied Economics*, 17 (1985), 713-744.

Taylor, S. J. "Rewards Available to Currency Futures Speculators: Compensation for Risk or Evidence of Inefficient Pricing?" *Economic Record*, 0 (1992), 105-116.

Taylor, S. J. "Trading Futures Using a Channel Rule: A Study of the Predictive Power of Technical Analysis with Currency Examples." *Journal of Futures Markets*, 14 (1994), 215-235.

Thaler, R. H. "Mental accounting and consumer choice." *Marketing Science*, 4 (1985), 199-214.

White, H. "A Reality Check for Data Snooping." *Econometrica*, 68 (2000), 1097-1126.

Table 1: Filter rule results for individual currencies: Sweeney (1986)

		filter sizes								filter sizes							
		0.5	1	2	3	4	5	10	mean	0.5	1	2	3	4	5	10	mean
DEM	Gross AR	7.24	9.89	10.54	5.41	8.74	7.90	-3.03	6.67	5.30	4.70	3.54	4.43	4.96	5.37	3.58	4.56
	Net AR	3.49	8.13	9.83	4.94	8.48	7.70	-3.16	5.63	2.46	3.21	2.84	4.08	4.73	5.22	3.53	3.72
	tstat	0.97	2.23	2.83	1.41	2.44	2.27	-0.93	1.60	1.12	1.45	1.30	1.86	2.13	2.35	1.60	1.69
	SR	0.33	0.75	0.99	0.49	0.87	0.83	-0.34	0.56	0.23	0.30	0.26	0.38	0.44	0.49	0.33	0.35
	(s.e.)	(0.33)	(0.33)	(0.34)	(0.34)	(0.35)	(0.42)	(0.38)	(0.36)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)
	TPY	41.45	19.46	7.87	5.25	3.03	2.24	1.46	11.54	57.25	30.25	13.78	7.20	4.39	3.01	0.98	16.69
	Brk stat									0.24	1.15	1.70	0.21	0.91	0.61	-1.65	
	BrkPV									0.40	0.12	0.04	0.42	0.18	0.27	0.95	
JPY	Gross AR	8.59	10.90	6.64	5.82	2.40	4.16	5.33	6.26	4.11	6.61	5.15	4.57	5.06	4.65	3.58	4.82
	Net AR	5.83	9.51	5.99	5.40	2.04	3.95	5.27	5.43	1.47	5.26	4.59	4.25	4.85	4.50	3.53	4.06
	tstat	1.76	2.84	1.73	1.51	0.59	1.14	1.57	1.59	0.65	2.37	2.05	1.93	2.23	2.02	1.58	1.83
	SR	0.67	1.09	0.63	0.55	0.21	0.44	0.61	0.60	0.13	0.49	0.40	0.40	0.45	0.42	0.31	0.37
	(s.e.)	(0.40)	(0.46)	(0.37)	(0.37)	(0.36)	(0.39)	(0.41)	(0.39)	(0.20)	(0.21)	(0.20)	(0.21)	(0.21)	(0.21)	(0.20)	(0.21)
	TPY	31.52	15.99	7.49	4.89	4.07	2.38	0.72	9.58	54.77	28.26	11.67	6.71	4.35	3.05	0.89	15.67
	Brk stat									1.09	1.06	0.34	0.27	-0.69	-0.13	0.43	
	BrkPV									0.14	0.15	0.37	0.39	0.75	0.55	0.33	
GBP	Gross AR	8.41	11.77	9.66	10.11	8.48	4.70	3.15	8.04	2.86	2.78	2.91	2.03	1.68	-0.29	3.92	2.27
	Net AR	5.45	10.59	9.16	9.83	8.28	4.50	3.08	7.27	0.13	1.34	2.32	1.69	1.45	-0.46	3.88	1.48
	tstat	1.88	3.54	3.14	3.38	2.87	1.47	1.01	2.47	0.06	0.63	1.11	0.82	0.70	-0.22	1.87	0.71
	SR	0.71	1.31	1.16	1.29	1.08	0.58	0.40	0.93	0.01	0.12	0.22	0.17	0.14	-0.04	0.38	0.14
	(s.e.)	(0.41)	(0.36)	(0.37)	(0.49)	(0.46)	(0.41)	(0.39)	(0.41)	(0.20)	(0.19)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)
	TPY	33.40	13.34	5.77	3.15	2.24	2.25	0.72	8.70	53.71	28.18	11.26	6.55	4.23	3.25	0.57	15.39
	Brk stat									1.50	2.52	1.90	2.29	1.92	1.34	-0.22	
	BrkPV									0.07	0.01	0.03	0.01	0.03	0.09	0.59	
CHF	Gross AR	10.63	15.49	8.56	11.49	8.78	4.29	1.95	8.74	0.31	1.26	3.61	3.78	5.47	1.54	6.11	3.15
	Net AR	6.09	13.34	7.50	10.93	8.37	3.93	1.82	7.42	-2.89	-0.50	2.87	3.35	5.21	1.33	6.06	2.21
	tstat	1.37	3.02	1.70	2.50	1.87	0.88	0.41	1.68	-1.17	-0.20	1.19	1.39	2.19	0.55	2.51	0.92
	SR	0.51	1.13	0.63	0.93	0.66	0.33	0.15	0.62	-0.24	-0.04	0.24	0.28	0.44	0.11	0.51	0.19
	SRse	(0.38)	(0.46)	(0.40)	(0.37)	(0.35)	(0.37)	(0.37)	(0.39)	(0.21)	(0.20)	(0.21)	(0.21)	(0.21)	(0.20)	(0.22)	(0.21)
	TPY	50.75	24.08	11.79	6.29	4.60	4.07	1.47	14.72	64.40	35.13	14.76	8.25	4.96	3.98	0.89	18.91
	Brk stat									1.77	2.74	0.92	1.52	0.62	0.51	-0.85	
	BrkPV									0.04	0.00	0.18	0.06	0.27	0.31	0.80	
FRF	Gross AR	9.56	11.02	7.74	6.91	7.53	4.38	-2.17	6.43	5.85	4.62	3.81	5.52	4.85	5.56	5.09	5.04
	Net AR	6.48	9.62	7.06	6.51	7.30	4.19	-2.28	5.55	3.10	3.20	3.15	5.17	4.62	5.41	5.04	4.24
	tstat	1.96	2.97	2.11	2.00	2.34	1.33	-0.72	1.71	1.42	1.45	1.43	2.33	2.08	2.47	2.32	1.93
	SR	0.74	1.10	0.81	0.75	0.86	0.48	-0.26	0.64	0.29	0.30	0.29	0.48	0.43	0.51	0.47	0.40
	(s.e.)	(0.41)	(0.46)	(0.42)	(0.41)	(0.36)	(0.38)	(0.37)	(0.40)	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.22)	(0.21)	(0.21)
	TPY	34.22	15.59	7.60	4.47	2.64	2.24	1.20	9.71	55.37	29.11	13.29	6.87	4.35	3.01	0.89	16.13
	Brk stat									0.85	1.64	0.98	0.34	0.70	-0.32	-1.90	
	BrkPV									0.20	0.05	0.16	0.37	0.24	0.63	0.97	

Notes: The left-hand panels display filter rule trading results from Sweeney's original sample period, 1973-1980. The right-hand panels display filter rule trading results from the later period, 1981-2005:6. Column headers describe filter sizes. The final column of each subpanel displays the mean of the columns. Gross AR is annual excess return; Net AR adjusts for the variable transaction cost, as described in the text. tstat uses Newey-West standard errors to test the null that the Net AR equals zero; SR is the annual Sharpe ratio. TPY gives the number of trades per year. The rows labeled "Brk stat" and "Brk PV" denote the t statistics and p-values for the null that the AR in the two periods are equal. Low p-values reject the null of equal mean AR between subsamples.

Table 1 (continued): Filter rule results for individual currencies: Sweeney (1986)

		filter sizes								filter sizes							
		0.5	1	2	3	4	5	10	mean	0.5	1	2	3	4	5	10	mean
CAD	Gross AR	4.80	5.25	2.13	-0.05	-1.34	0.81	2.33	1.99	0.54	0.76	-0.90	-0.67	0.59	1.06	1.86	0.46
	Net AR	3.56	4.83	1.91	-0.22	-1.46	0.76	2.33	1.67	-0.72	0.22	-1.11	-0.77	0.54	1.03	1.86	0.15
	tstat	2.53	3.55	1.34	-0.16	-1.06	0.39	1.06	1.09	-0.67	0.21	-1.01	-0.71	0.51	0.96	1.75	0.15
	SR	0.87	1.29	0.49	-0.06	-0.42	0.21	0.62	0.43	-0.14	0.04	-0.20	-0.15	0.10	0.20	0.36	0.03
	(s.e.)	(0.33)	(0.33)	(0.35)	(0.38)	(0.40)	(0.52)	(0.61)	(0.42)	(0.20)	(0.21)	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.20)
	TPY	14.23	4.79	2.47	1.90	1.35	0.52	0.00	3.61	28.66	12.68	4.92	2.48	1.22	0.73	0.12	7.26
	Brk stat									2.42	2.69	1.68	0.31	-1.15	-0.12	0.19	
	BrkPV									0.01	0.00	0.05	0.38	0.88	0.55	0.42	
ITL	Gross AR	12.13	8.23	4.21	4.37	3.29	0.21	3.17	5.09	7.39	4.12	3.33	5.76	7.16	6.10	2.58	5.21
	Net AR	9.95	6.97	3.60	4.02	3.05	0.02	3.14	4.39	4.80	2.69	2.71	5.43	6.97	5.96	2.53	4.44
	tstat	3.40	2.38	1.26	1.40	1.04	0.01	1.00	1.50	2.23	1.25	1.26	2.55	3.23	2.80	1.19	2.08
	SR	1.18	0.92	0.47	0.52	0.39	0.00	0.38	0.55	0.46	0.26	0.26	0.52	0.67	0.56	0.24	0.42
	(s.e.)	(0.31)	(0.43)	(0.36)	(0.35)	(0.36)	(0.36)	(0.37)	(0.36)	(0.21)	(0.21)	(0.21)	(0.22)	(0.22)	(0.20)	(0.20)	(0.21)
	TPY	24.39	14.07	6.75	3.84	2.65	2.12	0.29	7.73	52.85	29.31	12.56	6.46	3.74	2.76	1.06	15.54
	Brk stat									1.42	1.18	0.25	-0.40	-1.08	-1.60	0.16	
	BrkPV									0.08	0.12	0.40	0.65	0.86	0.95	0.44	
BEF	Gross AR	10.10	11.47	8.82	6.05	5.13	5.78	-1.69	6.52	2.39	1.79	3.10	5.85	5.94	5.23	5.37	4.24
	Net AR	7.00	10.04	8.14	5.61	4.84	5.58	-1.79	5.63	-0.51	0.24	2.41	5.51	5.72	5.08	5.32	3.40
	tstat	2.04	3.01	2.46	1.76	1.49	1.73	-0.56	1.70	-0.22	0.11	1.08	2.49	2.53	2.24	2.42	1.52
	SR	0.79	1.12	0.91	0.63	0.54	0.62	-0.20	0.63	-0.05	0.02	0.22	0.50	0.52	0.46	0.48	0.31
	(s.e.)	(0.41)	(0.46)	(0.43)	(0.40)	(0.39)	(0.40)	(0.37)	(0.41)	(0.20)	(0.20)	(0.20)	(0.21)	(0.22)	(0.21)	(0.21)	(0.21)
	TPY	34.50	15.99	7.60	4.99	3.29	2.24	1.20	9.97	58.22	31.39	13.86	6.95	4.23	3.09	0.89	16.95
	Brk stat									1.82	2.43	1.43	0.03	-0.22	0.13	-1.84	
	BrkPV									0.03	0.01	0.08	0.49	0.59	0.45	0.97	
ESP	Gross AR	5.78	5.23	9.17	10.37	8.35	6.39	5.91	7.31	2.63	1.98	3.04	4.78	5.69	5.90	4.34	4.05
	Net AR	4.23	4.50	9.00	10.27	8.25	6.29	5.88	6.92	-0.19	0.48	2.38	4.45	5.47	5.75	4.30	3.23
	tstat	1.21	1.27	2.64	2.55	2.05	1.35	1.27	1.76	-0.08	0.21	1.07	2.00	2.45	2.65	1.98	1.47
	SR	0.45	0.47	0.95	1.01	0.81	0.61	0.57	0.70	-0.02	0.04	0.22	0.41	0.50	0.53	0.40	0.30
	(s.e.)	(0.39)	(0.39)	(0.44)	(0.50)	(0.46)	(0.49)	(0.49)	(0.45)	(0.20)	(0.19)	(0.20)	(0.21)	(0.21)	(0.22)	(0.20)	(0.21)
	TPY	17.32	8.19	1.88	1.13	1.13	1.22	0.41	4.47	56.51	30.17	13.13	6.75	4.07	2.93	0.89	16.35
	Brk stat									1.06	0.95	1.62	1.27	0.60	0.11	0.31	
	BrkPV									0.15	0.17	0.05	0.10	0.27	0.46	0.38	
SEK	Gross AR	5.35	9.72	6.17	5.66	8.18	3.59	-6.90	4.54	2.35	3.35	2.54	1.27	1.31	3.93	6.13	2.98
	Net AR	2.45	8.59	5.60	5.35	8.02	3.44	-7.00	3.78	-0.25	2.02	1.99	0.96	1.10	3.81	6.11	2.25
	tstat	0.78	2.83	1.92	1.85	2.83	1.18	-2.44	1.28	-0.11	0.94	0.92	0.43	0.50	1.76	2.86	1.04
	SR	0.26	1.05	0.69	0.66	0.99	0.42	-0.87	0.46	-0.02	0.19	0.19	0.08	0.10	0.36	0.58	0.21
	(s.e.)	(0.34)	(0.45)	(0.40)	(0.40)	(0.44)	(0.38)	(0.43)	(0.41)	(0.20)	(0.20)	(0.20)	(0.19)	(0.20)	(0.21)	(0.22)	(0.20)
	TPY	31.90	12.45	6.29	3.42	1.71	1.71	1.07	8.36	54.64	28.38	11.91	6.63	4.31	2.60	0.61	15.58
	Brk stat									0.70	1.77	0.99	1.21	1.93	-0.10	-3.66	
	BrkPV									0.24	0.04	0.16	0.11	0.03	0.54	1.00	

Notes: See the notes to the first part of Table 1.

Table 2: Equally weighted portfolio rules for the rules and currencies examined by Sweeney (1986)

	DEM	JPY	GBP	CHF	FRF	CAD	ITL	BEF	ESP	SEK	mean
1973-1980											
Gross AR	6.58	5.99	7.83	8.64	6.34	1.65	4.99	6.43	6.02	4.48	5.89
Net AR	5.54	5.16	7.06	7.32	5.47	1.35	4.30	5.54	5.64	3.72	5.11
tstat	2.25	2.38	3.37	2.36	2.44	1.91	2.08	2.51	1.94	1.97	2.32
SR	0.76	0.83	1.28	0.86	0.87	0.68	0.76	0.91	0.69	0.69	0.84
(s.e.)	(0.30)	(0.32)	(0.49)	(0.32)	(0.32)	(0.33)	(0.30)	(0.34)	(0.40)	(0.31)	(0.34)
TPY	11.52	9.42	8.61	14.69	9.68	3.40	7.73	9.94	4.23	8.35	8.76
1981-2005:6											
Gross AR	4.56	4.82	2.27	3.15	5.04	0.46	5.21	4.24	4.05	2.98	3.68
Net AR	3.72	4.06	1.48	2.21	4.24	0.15	4.44	3.40	3.23	2.25	2.92
tstat	2.62	2.75	1.11	1.40	2.92	0.23	3.18	2.33	2.23	1.50	2.03
SR	0.54	0.54	0.22	0.29	0.60	0.05	0.65	0.47	0.45	0.30	0.41
(s.e.)	(0.22)	(0.18)	(0.19)	(0.21)	(0.22)	(0.20)	(0.22)	(0.21)	(0.21)	(0.19)	(0.21)
TPY	16.69	15.67	15.39	18.91	16.13	7.26	15.54	16.95	16.35	15.58	15.45
Test/PV											
Brk stat	0.64	0.42	2.25	1.47	0.46	1.26	-0.06	0.81	0.74	0.61	0.86
Brk PV	0.26	0.34	0.01	0.07	0.32	0.10	0.52	0.21	0.23	0.27	0.23

Notes: The top panel displays equally weighted portfolio rule results—over Sweeney's filter rules—from Sweeney's original sample period, 1973-1980. The center panel displays filter rule trading results from the later period, 1981-2005:6. Gross AR is annual excess return; Net AR adjusts for the variable transaction cost, as described in the text. IR is the annual information ratio. T stat is the t statistic for the null that the AR equals zero. SR is the Sharpe ratio (annual excess return divided by annual standard deviation of excess return). TPY is trades per year. Brk stat is the t statistic for the null that the AR of the first sample equals that in the second sample. Brk PV is the probability of obtaining at least as extreme of a t statistic under the null of equal means. Low p-values reject the null of equal mean AR between subsamples.

Table 3: Replication and Out-of-sample results for Levich and Thomas (1993) using spot exchange rates

		filter						moving averages				filter						moving averages			
		0.5	1	2	3	4	5	(1,5)	(5,20)	(1,200)	mean	0.5	1	2	3	4	5	(1,5)	(5,20)	(1,200)	mean
DEM	Gross AR	7.75	10.32	6.90	8.04	5.13	7.66	10.50	11.59	7.69	8.40	2.92	0.23	1.60	0.56	4.38	3.19	1.68	1.49	2.67	2.08
	Net AR	4.20	8.51	6.06	7.60	4.79	7.46	6.13	10.66	7.32	6.97	0.74	-0.91	1.10	0.28	4.23	3.08	-0.81	0.93	2.37	1.22
	tstat	1.53	3.06	2.23	2.81	1.70	2.64	2.32	3.87	2.55	2.52	0.27	-0.33	0.41	0.10	1.52	1.10	-0.29	0.34	0.87	0.44
	SR	0.41	0.83	0.59	0.74	0.46	0.71	0.63	1.03	0.70	0.68	0.07	-0.09	0.11	0.03	0.41	0.29	-0.08	0.09	0.23	0.12
	(s.e.)	(0.27)	(0.30)	(0.28)	(0.29)	(0.28)	(0.30)	(0.27)	(0.32)	(0.30)	(0.29)	(0.26)	(0.26)	(0.26)	(0.26)	(0.27)	(0.27)	(0.26)	(0.26)	(0.27)	(0.27)
	TPY	49.22	25.27	11.85	6.10	4.65	2.79	59.02	12.63	5.05	19.62	58.09	30.66	13.10	7.34	3.84	2.95	66.94	15.50	8.85	23.03
	Brk stat											0.89	2.40	1.29	1.90	0.14	1.10	1.81	2.50	1.25	
	BrkPV											0.19	0.01	0.10	0.03	0.44	0.13	0.04	0.01	0.11	
JPY	Gross AR	9.47	14.15	8.46	8.33	8.04	7.40	9.70	11.73	10.15	9.72	0.96	1.61	1.86	1.67	1.84	2.81	1.41	3.37	0.51	1.78
	Net AR	6.08	12.48	7.70	7.88	7.73	7.19	5.28	10.81	9.90	8.34	-1.11	0.49	1.42	1.41	1.67	2.69	-1.02	2.81	0.23	0.95
	tstat	2.18	4.57	2.74	2.82	2.76	2.52	1.96	3.98	3.46	3.00	-0.37	0.17	0.48	0.49	0.59	0.93	-0.35	0.98	0.08	0.33
	SR	0.54	1.16	0.68	0.72	0.70	0.64	0.53	1.00	0.89	0.76	-0.10	0.04	0.13	0.13	0.15	0.24	-0.09	0.25	0.02	0.09
	(s.e.)	(0.25)	(0.25)	(0.25)	(0.26)	(0.25)	(0.25)	(0.28)	(0.25)	(0.26)	0.25	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)	(0.27)	(0.27)	(0.27)	(0.26)	(0.26)
	TPY	46.74	23.08	10.49	6.12	4.21	2.98	59.95	12.89	3.51	18.89	57.41	30.45	12.21	7.13	4.66	3.02	65.91	15.23	8.44	22.72
	Brk stat											1.76	3.00	1.54	1.61	1.53	1.11	1.58	2.03	2.37	
	BrkPV											0.04	0.00	0.06	0.05	0.06	0.13	0.06	0.02	0.01	
CHF	Gross AR	5.40	8.51	9.11	8.01	8.50	2.68	8.38	8.43	9.26	7.59	-1.72	-2.20	-0.69	2.07	3.34	0.06	-3.31	-0.65	0.16	-0.33
	Net AR	1.13	6.22	8.11	7.43	8.11	2.35	3.73	7.46	8.87	5.93	-4.15	-3.51	-1.22	1.78	3.17	-0.08	-5.91	-1.27	-0.18	-1.26
	tstat	0.34	1.94	2.60	2.34	2.49	0.71	1.17	2.32	2.65	1.84	-1.35	-1.11	-0.40	0.59	1.07	-0.03	-1.89	-0.43	-0.06	-0.40
	SR	0.09	0.51	0.67	0.61	0.67	0.19	0.31	0.62	0.72	0.49	-0.36	-0.29	-0.11	0.15	0.28	-0.01	-0.51	-0.11	-0.02	-0.11
	(s.e.)	(0.26)	(0.28)	(0.29)	(0.28)	(0.29)	(0.26)	(0.27)	(0.28)	(0.30)	0.28	(0.27)	(0.26)	(0.26)	(0.26)	(0.27)	(0.26)	(0.28)	(0.26)	(0.26)	(0.27)
	TPY	58.93	31.72	13.87	8.02	5.23	4.42	63.02	13.16	5.19	22.62	64.68	34.91	14.33	7.68	4.53	3.70	70.16	16.74	9.81	25.17
	Brk stat											1.18	2.16	2.13	1.29	1.12	0.54	2.16	2.00	2.01	
	BrkPV											0.12	0.02	0.02	0.10	0.13	0.29	0.02	0.02	0.02	
GBP	Gross AR	8.79	8.49	8.27	7.42	6.36	2.99	12.01	8.36	7.52	7.80	-0.68	0.34	-0.66	-0.88	-0.40	-2.01	0.70	-1.82	-0.27	-0.63
	Net AR	5.18	6.65	7.49	6.96	6.06	2.74	7.76	7.43	7.22	6.39	-2.62	-0.65	-1.06	-1.10	-0.54	-2.12	-1.82	-2.44	-0.60	-1.44
	tstat	1.89	2.30	2.66	2.49	2.19	0.97	2.82	2.63	2.47	2.27	-1.08	-0.26	-0.43	-0.46	-0.22	-0.88	-0.74	-1.02	-0.25	-0.59
	SR	0.49	0.59	0.70	0.66	0.58	0.25	0.75	0.71	0.65	0.60	-0.27	-0.07	-0.12	-0.12	-0.06	-0.24	-0.19	-0.28	-0.07	-0.16
	(s.e.)	(0.28)	(0.25)	(0.26)	(0.29)	(0.28)	(0.26)	(0.26)	(0.29)	(0.27)	0.27	(0.26)	(0.25)	(0.26)	(0.26)	(0.26)	(0.27)	(0.25)	(0.27)	(0.27)	(0.26)
	TPY	50.09	25.89	10.90	6.46	4.31	3.50	57.76	12.63	4.07	19.51	51.23	26.27	10.22	5.76	3.57	2.74	67.70	16.60	8.98	21.45
	Brk stat											2.13	1.92	2.29	2.20	1.79	1.31	2.60	2.67	2.08	
	BrkPV											0.02	0.03	0.01	0.01	0.04	0.10	0.00	0.00	0.02	

Notes: See the notes to Table 1.

Table 4: Equally weighted portfolio rules for the rules and currencies examined by Levich and Thomas (1993)

	DEM	JPY	CHF	GBP	mean
1976-1990					
Gross AR	8.26	9.52	7.48	7.70	8.24
Net AR	6.88	8.18	5.86	6.32	6.81
tstat	3.66	4.35	2.71	3.34	3.51
SR	0.96	1.06	0.71	0.88	0.90
(s.e.)	(0.31)	(0.22)	(0.29)	(0.30)	(0.28)
TPY	18.99	18.37	22.08	18.96	19.60
1991-2005:6					
Gross AR	2.08	1.78	-0.33	-0.63	0.73
Net AR	1.25	0.97	-1.24	-1.42	-0.11
tstat	0.71	0.51	-0.64	-0.90	-0.08
SR	0.19	0.14	-0.17	-0.23	-0.02
(s.e.)	(0.27)	(0.26)	(0.26)	(0.26)	(0.26)
TPY	22.28	22.25	24.61	21.01	22.54
Test/PV					
Brk stat	2.18	2.68	2.44	3.15	2.61
Brk PV	0.01	0.00	0.01	0.00	0.01

Notes: The results refer to results from equally weighted portfolio rules for the rules and currencies examined by Levich and Thomas (1993), with an original sample of 1976 through 1990 and a subsequent sample of 1991 through 2005:6. See the notes to Table 2 for the row headings.

Table 5: Results from channel rules examined by Taylor (1994)

	DEM/USD	JPY/USD	CHF/USD	GBP/USD	mean
1982-1990					
Gross AR	7.50	10.98	4.46	5.55	7.12
Net AR	6.15	9.67	3.05	4.09	5.74
tstat	1.64	2.59	0.76	1.07	1.51
SR	0.57	0.80	0.26	0.36	0.50
(s.e.)	(0.36)	(0.30)	(0.34)	(0.34)	(0.34)
TPY	20.04	19.49	20.70	21.81	20.51
1991-2005:6					
Gross AR	3.34	0.33	3.53	1.40	2.15
Net AR	3.15	0.00	3.41	1.09	1.91
tstat	1.18	0.00	1.13	0.46	0.69
SR	0.30	0.00	0.30	0.12	0.18
(s.e.)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
TPY	4.66	8.63	3.43	7.27	6.00
Test/PV					
Brk stat	0.65	2.06	-0.07	0.67	0.83
Brk PV	0.26	0.02	0.53	0.25	0.26

Notes: The results refer to results from channel rules, computed over rolling samples to optimize the window length, with an original sample of 1982 through 1990 and a subsequent sample of 1991 through 2005:6. See the notes to Table 2 for the row headings.

Table 6: Results from ARIMA rules examined by Taylor (1994)

	DEM/USD	JPY/USD	CHF/USD	GBP/USD	mean
1979-1987:11					
Gross AR	7.68	8.76	6.44	7.24	7.53
Net AR	7.24	8.35	5.98	6.80	7.09
tstat	2.10	2.57	1.54	1.95	2.04
SR	0.72	0.82	0.54	0.68	0.69
(s.e.)	(0.38)	(0.32)	(0.36)	(0.37)	(0.36)
TPY	6.10	5.54	6.32	5.99	5.99
1987:12-2005:6					
Gross AR	3.20	4.77	3.37	1.64	3.24
Net AR	2.91	4.50	3.11	1.35	2.97
tstat	1.30	1.87	1.30	0.68	1.29
SR	0.31	0.45	0.31	0.16	0.31
(s.e.)	(0.24)	(0.23)	(0.24)	(0.24)	(0.24)
TPY	6.86	6.68	6.52	7.25	6.83
Test/PV					
T stat	1.05	0.95	0.63	1.36	1.00
P-value	0.15	0.17	0.26	0.09	0.17

Notes: The results refer to results from ARIMA(1,0,2) rules, computed with an original sample of 1979 through 1987:11 and a subsequent sample of 1987:12 through 2005:6. See the notes to Table 2 for the row headings.

Table 7: Equally weighted portfolio rules for the genetic programming rules of NWD (1997)

	DEM/USD	JPY/USD	GBP/USD	CHF/USD	DEM/JPY	GBP/CHF	mean
1981-1995:10							
Gross AR	6.41	2.71	2.72	1.95	5.48	1.21	3.42
Net AR	6.10	2.39	2.35	1.64	4.13	1.04	2.94
tstat	2.37	1.29	0.97	0.71	2.51	0.50	1.39
SR	0.59	0.33	0.26	0.18	0.67	0.13	0.36
(s.e.)	(0.25)	(0.25)	(0.26)	(0.25)	(0.29)	(0.26)	(0.26)
TPY	5.04	5.39	5.76	5.00	21.95	2.68	7.64
% > 0	98	68	92	87	92	92	88.17
1995:10-2005:6							
Gross AR	4.84	0.57	1.57	-2.34	-0.34	-1.98	0.39
Net AR	4.68	0.40	1.44	-2.48	-1.13	-2.03	0.15
tstat	1.81	0.17	0.68	-1.08	-0.44	-0.84	0.05
SR	0.58	0.06	0.22	-0.35	-0.14	-0.26	0.02
(s.e.)	(0.35)	(0.32)	(0.32)	(0.32)	(0.32)	(0.33)	(0.33)
TPY	5.38	5.35	3.89	4.69	25.58	1.62	7.75
% > 0	95	50	84	20	53	8	51.67
Test/PV							
Brk stat	0.39	0.67	0.28	1.27	1.73	0.96	0.88
Brk PV	0.35	0.25	0.39	0.10	0.04	0.17	0.22

Notes: The results refer to results from genetic programming rules, optimized over an in-sample period (1975-1980), with an original out-of-sample period of 1981 through October 11, 1995 (top panel) and a subsequent sample of October 12, 1995 through 2005:6 (center panel). The notes to Table 2 describe the row headings, except for "% > 0", which describes the percentage of the 100 genetic programming rules in each period that had positive returns in the respective samples.

Table 8: Results for the Markov model rules of Dueker and Neely (2007).

	DEM/USD	JPY/USD	CHF/USD	GBP/USD	mean
1982/83-1998					
Gross AR	7.08	10.97	7.77	0.32	6.53
Net AR	6.46	10.60	7.65	0.24	6.24
tstat	2.44	3.78	2.58	0.09	2.22
SR	0.60	0.95	0.63	0.02	0.55
(s.e.)	(0.26)	(0.24)	(0.27)	(0.24)	(0.25)
TPY	10.96	6.60	2.11	1.47	5.28
1999-2005:6					
Gross AR	6.37	0.37	1.96	3.43	3.03
Net AR	6.12	0.10	1.91	3.35	2.87
tstat	1.57	0.03	0.47	1.08	0.79
SR	0.61	0.01	0.18	0.41	0.30
(s.e.)	(0.43)	(0.39)	(0.40)	(0.41)	(0.41)
TPY	9.22	10.60	1.69	2.77	6.07
Test/PV					
Brk stat	0.07	2.19	1.14	-0.76	0.66
Brk PV	0.47	0.01	0.13	0.78	0.35

Notes: The results refer to results from trading rules based on a Markov switching model, estimated over an in-sample period (1975-1981, 1975-1982 for the JPY), with an original out-of-sample period through 1998 (top panel) and a subsequent sample of 1999 through 2005:6 (center panel). The notes to Table 2 describe the row headings.

Table 9: Estimated time trends in uniform portfolio rule returns

Sweeney (1986) 1973:4-2005:6											
	DEM	JPY	GBP	CHF	FRF	CAD	ITL	BEF	ESP	SEK	mean
const	7.47	7.38	8.35	8.96	8.27	1.76	7.05	8.03	5.87	5.49	6.86
(s.e.)	(2.40)	(2.34)	(2.17)	(2.77)	(2.40)	(1.01)	(2.29)	(2.44)	(2.61)	(2.38)	(2.28)
trend	-0.20	-0.19	-0.34	-0.34	-0.23	-0.08	-0.16	-0.25	-0.13	-0.18	-0.21
(s.e.)	(0.13)	(0.13)	(0.12)	(0.15)	(0.13)	(0.05)	(0.12)	(0.13)	(0.14)	(0.13)	(0.12)

Levich and Thomas (1993) 1976-2005:6					
	DEM	JPY	CHF	GBP	mean
const	7.66	10.19	7.82	8.67	8.58
(s.e.)	(2.54)	(2.56)	(2.88)	(2.39)	(2.59)
trend	-0.24	-0.38	-0.37	-0.42	-0.35
(s.e.)	(0.15)	(0.15)	(0.17)	(0.14)	(0.15)

Taylor (1994) Channel Rules 1982-2005:6					
	DEM	JPY	CHF	GBP	mean
const	7.90	12.03	4.89	4.60	7.35
(s.e.)	(4.35)	(4.40)	(4.81)	(4.05)	(4.40)
trend	-0.31	-0.71	-0.14	-0.20	-0.34
(s.e.)	(0.32)	(0.32)	(0.35)	(0.30)	(0.32)

Taylor (1994) ARIMA Rules 1979-2005:6					
	DEM	JPY	CHF	GBP	mean
const	7.79	9.62	7.79	9.12	8.58
(s.e.)	(3.73)	(3.74)	(4.06)	(3.45)	(3.75)
trend	-0.26	-0.29	-0.28	-0.45	-0.32
(s.e.)	(0.24)	(0.24)	(0.26)	(0.22)	(0.24)

NWD (1997) genetic programming rules 1981-2005:6							
	DEM/USD	JPY/USD	USD/GBP	CHF/USD	DEM/JPY	GBP/CHF	mean
const	8.06	1.89	2.26	-0.64	6.47	0.37	3.07
(s.e.)	(3.68)	(2.89)	(3.31)	(3.31)	(2.81)	(3.17)	(3.20)
trend	-0.21	-0.02	-0.02	0.05	-0.36	-0.05	-0.10
(s.e.)	(0.26)	(0.20)	(0.23)	(0.23)	(0.20)	(0.22)	(0.23)

Dueker and Neely (2006) 1982/83-2005:6					
	DEM	JPY	CHF	GBP	mean
const	9.75	12.90	10.44	0.55	8.41
(s.e.)	(4.36)	(4.47)	(4.82)	(4.06)	(4.43)
trend	-0.29	-0.47	-0.37	0.05	-0.27
(s.e.)	(0.32)	(0.34)	(0.35)	(0.30)	(0.33)

Notes: The table displays the results of regressing annualized daily trading rule returns from the uniform portfolio rule on a constant and a time trend. The "ttrend" coefficients can be interpreted as the expected annual decline in annual net returns to the uniform portfolio rules. Annual returns are measured in percentage points.

Table 10: Risk adjustment of trading rule returns by the CAPM

Sweeney (1986)	GBP	SEK	JPY	ITL	ESP	CHF	FRF	DEM	CAD	BEF
1973-2005:6										
alpha	3.08	2.88	4.79	4.22	4.55	3.86	4.34	4.10	0.52	4.33
(s.e)	(1.16)	(1.26)	(1.27)	(1.24)	(1.39)	(1.47)	(1.26)	(1.27)	(0.55)	(1.30)
beta	-0.02	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02
(s.e)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)

Levich and Thomas (1993)	DEM	JPY	CHF	GBP
1976-2005:6				
alpha	4.27	4.74	2.53	2.65
(s.e)	(1.27)	(1.28)	(1.44)	(1.20)
beta	-0.02	-0.02	-0.03	-0.02
(s.e)	(0.01)	(0.01)	(0.01)	(0.00)

Taylor (1994) Channel Rules	DEM	JPY	CHF	GBP
1976-2005:6				
alpha	4.47	3.84	3.44	2.35
(s.e)	(2.18)	(2.20)	(2.41)	(2.03)
beta	-0.02	-0.02	-0.02	-0.02
(s.e)	(0.01)	(0.01)	(0.01)	(0.01)

Taylor (1994) ARIMA Rules	DEM	JPY	CHF	GBP
1979-2005:6				
alpha	4.35	5.89	4.06	3.19
(s.e)	(1.87)	(1.87)	(2.03)	(1.73)
beta	0.00	-0.01	0.00	0.00
(s.e)	(0.01)	(0.01)	(0.01)	(0.01)

NWD (1997) genetic programming rules	DEM/USD	JPY/USD	USD/GBP	CHF/USD	DEM/JPY	GBP/CHF
1981-2005:6						
alpha	7.79	3.19	2.75	1.17	3.20	1.17
(s.e)	(2.55)	(2.01)	(2.29)	(2.29)	(1.95)	(2.19)
beta	-0.04	-0.03	-0.06	-0.06	-0.01	-0.04
(s.e)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Dueker and Neely (2006)	DEM	JPY	CHF	GBP
1982/83-2005:6				
alpha	6.65	7.88	6.63	1.16
(s.e)	(2.18)	(2.23)	(2.40)	(2.03)
beta	-0.04	-0.04	-0.06	0.00
(s.e)	(0.01)	(0.01)	(0.01)	(0.01)

Notes: The table displays Jensen's α and the CAPM βs from regressions of the uniform trading rule excess returns for each study on the total excess return to the U.S. MSCI index.

Table 11: Model selection

		constant	Mean Break	Time trend	constant	Mean Break	Time trend	BestH0
Sweeney	DEM/USD	0.00	-8.60	-6.54	-2.46	-2.06	0.00	constant
Sweeney	JPY/USD	0.00	-8.85	-7.04	-1.96	-1.81	0.00	constant
Sweeney	GBP/USD	0.00	-4.56	-1.05	-7.95	-3.51	0.00	Time trend
Sweeney	CHF/USD	0.00	-6.61	-3.86	-5.14	-2.75	0.00	Time trend
Sweeney	FRF/USD	0.00	-8.82	-5.83	-3.16	-2.98	0.00	constant
Sweeney	CAD/USD	0.00	-8.04	-6.77	-2.22	-1.27	0.00	constant
Sweeney	ITL/USD	0.00	-9.00	-7.33	-1.67	-1.67	0.00	constant
Sweeney	BEF/USD	0.00	-8.46	-5.27	-3.72	-3.18	0.00	constant
Sweeney	ESP/USD	0.00	-8.36	-8.16	-0.84	-0.21	0.00	constant
Sweeney	SEK/USD	0.00	-8.73	-7.12	-1.88	-1.61	0.00	constant
L&T	DEM/USD	0.00	-4.06	-6.37	-4.85	0.00	-2.31	Mean Break
L&T	JPY/USD	0.00	-1.44	-3.17	-7.47	0.00	-1.73	Mean Break
L&T	CHF/USD	0.00	-2.77	-4.30	-6.14	0.00	-1.53	Mean Break
L&T	GBP/USD	-0.87	0.00	-1.60	-9.78	0.00	-1.60	Mean Break
Taylor (C)	DEM/USD	0.00	-8.24	-7.78	-0.90	-0.46	0.00	constant
Taylor (C)	JPY/USD	0.00	-4.53	-4.26	-4.43	-0.28	0.00	Time trend
Taylor (C)	CHF/USD	0.00	-8.68	-8.54	-0.15	-0.14	0.00	constant
Taylor (C)	GBP/USD	0.00	-8.19	-8.26	-0.50	0.00	-0.08	constant
Taylor (A)	DEM/USD	0.00	-7.82	-7.90	-0.98	0.00	-0.08	constant
Taylor (A)	JPY/USD	0.00	-7.93	-7.51	-1.29	-0.42	0.00	constant
Taylor (A)	CHF/USD	0.00	-8.37	-7.71	-1.09	-0.66	0.00	constant
Taylor (A)	GBP/USD	0.00	-6.73	-5.12	-3.68	-1.61	0.00	constant
NWD	DEM/USD	0.00	-8.95	-8.46	-0.64	-0.50	0.00	constant
NWD	JPY/USD	0.00	-8.63	-9.08	-0.47	0.00	-0.45	constant
NWD	USD/GBP	0.00	-9.04	-9.09	-0.06	0.00	-0.05	constant
NWD	CHF/USD	0.00	-7.52	-9.05	-1.58	0.00	-1.53	constant
NWD	JPY/DEM	0.00	-5.77	-5.82	-3.33	0.00	-0.04	constant
NWD	CHF/GBP	0.00	-8.17	-9.06	-0.93	0.00	-0.89	constant
DN	DEM/USD	0.00	-8.68	-7.88	-0.80	-0.79	0.00	constant
DN	JPY/USD	0.00	-4.39	-6.87	-4.24	0.00	-2.48	Mean Break
DN	CHF/USD	0.00	-7.57	-7.60	-1.11	0.00	-0.03	constant
DN	GBP/USD	0.00	-8.26	-8.66	-0.42	0.00	-0.40	constant

Notes: The table describes relative Schwarz criteria and twice the log likelihood differences for the uniform portfolio rule returns under three models: 1) constant mean; 2) a break in the mean return at the end of the original sample; 3) a time trend in returns. The left-hand panel shows the Schwarz criterion of each model relative to the best model, which will have a normalized SC of zero. The right-hand panel shows the log likelihoods of each model relative to the best model, which will have a normalized log likelihood of zero. The column labeled BestH0 summarizes the evidence from the log likelihoods. It will have either the model with the highest log likelihood (the mean break or time trend) or the constant model if one cannot reject that restriction. The original sample periods were April 1973 through 1980, 1976 though 1990, 1982 through 1990, 1979 though 1987:11, 1981 through October 10, 1995, 1982/83-1998 for Sweeney, Levich and Thomas, Taylor (1994) channel rules, Taylor (1994) ARIMA models, NWD, and Dueker and Neely, respectively.

Table 12: Andrews (1993) tests for a structural break at an unknown point

Sample		Sup Lambda	p-value	Break date
Sweeney	DEM	6.17	0.15	19910422
Sweeney	JPY	7.53	**0.09**	19990915
Sweeney	GBP	18.86	**0.00**	19921110
Sweeney	CHF	8.33	**0.06**	19900823
Sweeney	FRF	5.44	0.22	19910422
Sweeney	CAD	8.01	**0.08**	19781003
Sweeney	ITL	4.69	0.30	19931202
Sweeney	BEF	8.08	**0.07**	19910422
Sweeney	ESP	2.74	0.64	19860225
Sweeney	SEK	5.28	0.23	19930112
LT	DEM	7.35	0.11	19910327
LT	JPY	10.51	**0.02**	19990915
LT	CHF	8.66	**0.05**	19890522
LT	GBP	18.56	**0.00**	19921110
Taylor (C)	DEM	3.03	0.54	19860530
Taylor (C)	JPY	6.73	0.12	19890615
Taylor (C)	CHF	1.68	0.84	19860304
Taylor (C)	GBP	2.56	0.66	19930426
Taylor (A)	DEM	4.10	0.38	19850222
Taylor (A)	JPY	7.64	**0.08**	19990108
Taylor (A)	CHF	2.28	0.73	19890519
Taylor (A)	GBP	10.52	**0.02**	19930423
NWD	DEM	2.08	0.78	19910702
NWD	JPY	3.51	0.48	19850610
NWD	GBP	2.55	0.67	20011023
NWD	CHF	9.50	**0.04**	19850225
NWD	JPY/DEM	4.11	0.37	20010111
NWD	CHF/GBP	1.57	0.90	19861010
DN	DEM	4.87	0.29	19920902
DN	JPY	6.68	0.12	19981019
DN	CHF	3.34	0.50	19921005
DN	GBP	2.95	0.60	19920908

Notes: The table shows the results of an Andrews (1993) test for a structural break in the mean return to uniform-rule TTRs at an unknown point. The first two columns show the original study and exchange rate. Columns 3 through 5 show the maximum Wald structural break statistic over the middle 70 percent of the sample, its p-value and the date on which it occurred. Bold p-values are less than 0.1. All samples ended in June 2005. The sample starting points were as follows: Sweeney: 4/2/1973; Levich and Thomas: 1/2/1976; Taylor (C): 1/4/1982; Taylor (A): 1/4/1979; NWD: 1/2/1981; and Dueker and Neely: 1/3/1983.

Table 13: Citation Count by Year

	Sweeney (1986)	Levich and Thomas (1993)	Taylor (1994)	NWD (1997)	Dueker and Neely (2006)
1985					
1986	2				
1987	1				
1988					
1989	1				
1990					
1991					
1992	2		1		
1993	2	2			
1994	1	1			
1995	3	2			
1996	5	5	2		
1997	2	4	1		
1998	2	3		1	
1999	8	8	2		
2000	5	5	2	5	
2001	2	1	2	6	
2002	2	6	1	3	
2003	4	5	1	4	
2004	5	7		12	1
2005	1	2		5	
2006	1	1		5	4
Sum	49	52	12	41	5

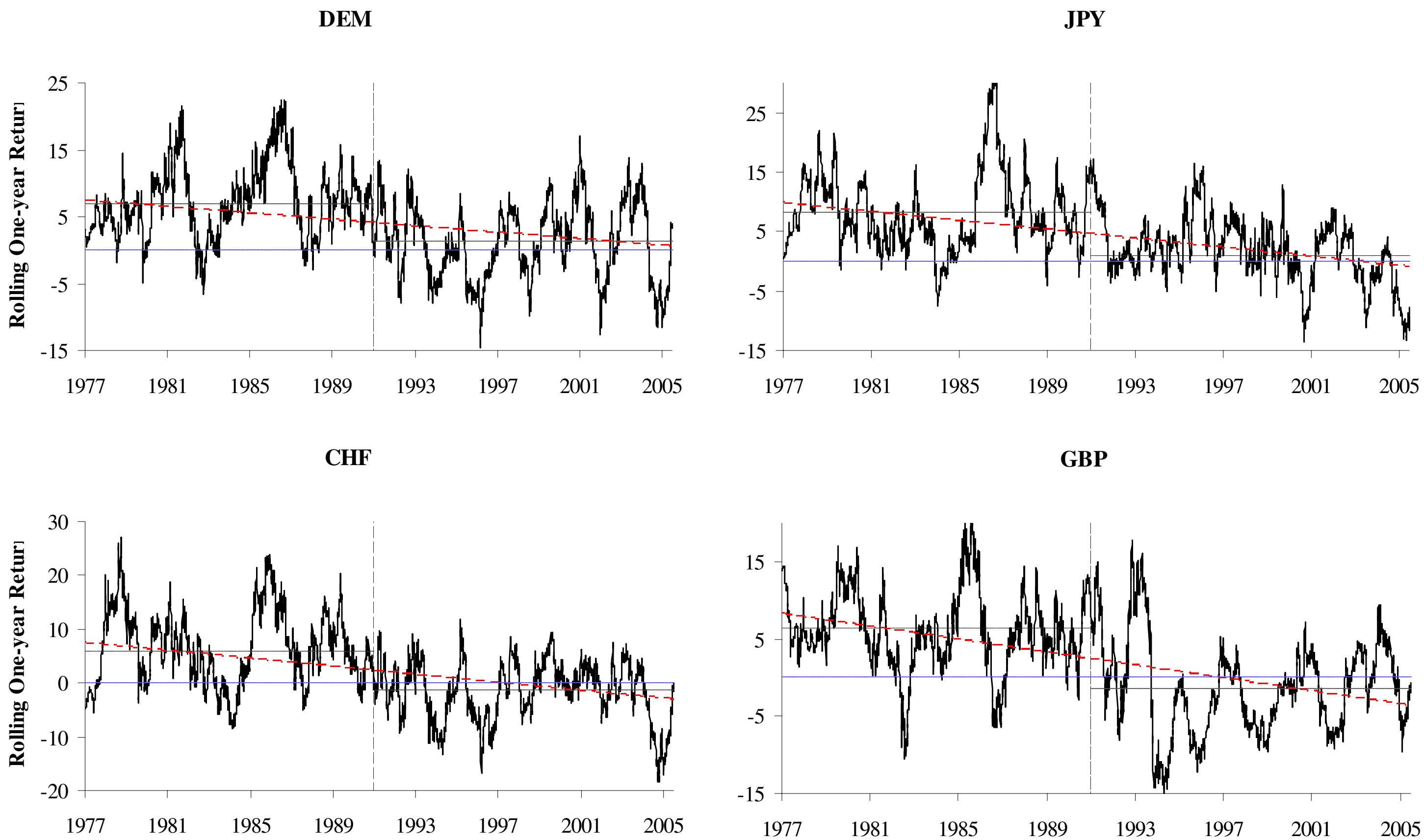
Notes: The Web of Knowledge was used to search the Social Science Citation Index for the period of 1995-present, while Dialogue was used to search the period from 1986 to 1995. To supplement the pre-1996 electronic search, which produced sparse results, we manually searched all articles, dated from 1986 to 1995, which were cited in Menkhoff and Taylor's (2006) literature survey.

Table 14: Characteristics of Combined Portfolio: MSCI (U.S.) and Levich and Thomas equally weighted returns

	DEM	JPY	CHF	GBP	mean
1976-1990					
MSCI net AR	4.67	4.67	4.67	4.67	4.67
TTR net AR	6.88	8.19	5.86	6.32	6.81
Portfolio net AR	16.00	19.81	12.25	14.69	15.69
(s.e.)	(4.14)	(4.40)	(4.11)	(4.11)	(4.19)
t stat	3.87	4.50	2.98	3.58	3.73
SR	1.03	1.10	0.79	0.95	0.96
(s.e.)	(0.32)	(0.22)	(0.30)	(0.31)	(0.29)
MSCI weight	0.35	0.27	0.44	0.37	0.36
TTR weight	2.09	2.26	1.74	2.05	2.04
1991-2005:6					
MSCI net AR	8.43	8.43	8.43	8.43	8.43
TTR net AR	1.25	0.97	-1.25	-1.42	-0.11
Portfolio net AR	5.56	4.52	1.51	0.17	2.94
(s.e.)	(3.91)	(4.42)	(3.75)	(3.46)	(3.89)
t stat	1.42	1.02	0.40	0.05	0.72
SR	0.38	0.27	0.11	0.01	0.19
(s.e.)	(0.27)	(0.27)	(0.26)	(0.26)	(0.27)

Notes: The rows of the top panel show the annual excess return for the MSCI (U.S.) index, the annual net return for the TTR (from Table 4), the annual net return to the optimal combined portfolio, the Newey-West standard error for the portfolio return, the t-statistic for the null that the net portfolio return is zero, the Sharpe ratio of the portfolio return, the standard error of that Sharpe ratio and the portfolio weights for the MSCI index and the TTR. The rows of the bottom panel omit repeating the portfolio weights.

Figure 1: Backward-looking rolling one-year returns to the uniform portfolio rules constructed from Levich and Thomas' (1993) study



Notes: The horizontal lines denote the original sample (1976-1990) mean return, the subsequent sample return (1991-2005:6), and a zero line. The vertical line denotes the end of the original sample (1991). The diagonal line represents the fitted values of the rule returns from a regression with a constant and the time trend.